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ASSESSMENT OF HOUSEHOLD CARBON FOOTPRINT REDUCTION POTENTIALS

PIER FINAL PROJECT REPORT

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Preface

The Public Interest Energy Research (PIER) Program supports public interest energy research and development that will help improve the quality of life in California by bringing environmentally safe, affordable, and reliable energy services and products to the marketplace. The PIER Program, managed by the California Energy Commission (Energy Commission), conducts public interest research, development, and demonstration (RD&D) projects to benefit California.

The PIER Program strives to conduct the most promising public interest energy research by partnering with RD&D entities, including individuals, businesses, utilities, and public or private research institutions.

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Assessment of Household Carbon Footprint Reduction Potentials is the final report for the Assessment of Household Carbon Footprint Reduction Potential project (contract number UC 500-02-004, work authorization number MR-069) conducted by Lawrence Berkeley National Laboratory. The information from this project contributes to PIER's Energy-Related Environmental Research Program.
For more information about the PIER Program, please visit the Energy Commission's website at www.energy.ca.gov/pier or contact the Energy Commission at 916-654-5164

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Abstract and Keywords

The term "household carbon footprint" refers to the total annual carbon emissions associated with household consumption of energy, goods, and services. In this project, Lawrence Berkeley National Laboratory developed a carbon footprint modeling framework that characterizes the key underlying technologies and processes that contribute to household carbon footprints in California and the United States. The approach breaks down the carbon footprint by 35 different household fuel end uses and 32 different supply chain fuel end uses. This level of end use detail allows energy and policy analysts to better understand the underlying technologies and processes contributing to the carbon footprint of California households. The modeling framework was applied to estimate the annual home energy and supply chain carbon footprints of a prototypical California household. A preliminary assessment of parameter uncertainty associated with key model input data was also conducted. To illustrate the policy-relevance of this modeling framework, a case study was conducted that analyzed the achievable carbon footprint reductions associated with the adoption of energy efficient household and supply chain technologies.

Keywords: life-cycle assessment, climate change, embodied energy, embodied carbon, input-output analysis, supply chain management, energy efficiency

1.0 Executive Summary

Introduction

There is growing interest in the development of tools and methods for calculating the "carbon footprint" associated with household consumption. In this project, Lawrence Berkeley National Laboratory developed a carbon footprint modeling framework that characterizes the key underlying technologies and processes that contribute to household carbon footprints in California and the United States.

Purpose

The main goal of this project was to develop and demonstrate a carbon footprint modeling framework that is more useful for policy analysis than existing carbon footprint calculator tools. Specifically, the research team aimed to develop a modeling framework with greater bottom-up detail than existing tools, which would allow energy and policy analysts to better understand the underlying technologies and processes contributing to the carbon footprint of California households. This detail also facilitates the analysis of specific technology improvement options for reducing the household carbon footprints in California.

Project Objectives

In support of this goal, the project had three primary objectives: (1) to compile information sufficient to characterize the annual household consumption of energy, goods, and services by California residents; (2) to develop a modeling framework to estimate the carbon footprint associated with these consumption activities; and (3) to analyze some policy-relevant options for reducing the carbon footprints of California residents.

Project Outcomes

The carbon footprint modeling framework developed in this project has two primary components: a direct household emissions modeling component and a supply chain emissions modeling component. The direct household emissions model estimates the annual carbon emissions associated with household energy use in California, which is attributable to various end uses for electricity and natural gas (e.g., space heating, appliances, lighting, and entertainment equipment). The supply chain emissions modeling component estimates the annual carbon emissions associated with the purchase of household goods and services.

The direct household emissions model was developed using California residential energy end use data from the California Residential Appliance Saturation Survey. The resulting modeling framework disaggregates California household energy use into 28 electricity end use technologies and 7 natural gas end use technologies. Annual carbon emissions arising from household electricity use were calculated using a California-specific emission factor, which takes into account the carbon intensity of electricity imports. A preliminary parameter uncertainty analysis was conducted for key variables in the modeling framework to aid in results interpretation.

The supply chain emissions model characterizes the annual greenhouse gas (GHG) emissions associated with 32 underlying fuel end uses in key supply chain sectors (e.g., manufacturing, commercial, agricultural, and water treatment). A preliminary parameter uncertainty assessment was conducted for key supply chain modeling data to aid in results interpretation.

The supply chain modeling framework was coupled with data representative of annual U.S. household expenditures to approximate the total supply chain GHG emissions associated with the purchase of goods and services of California households.

The results for the estimated average direct home energy and supply chain carbon footprints of a prototypical California household are summarized in Figure ES-1. The error bars in this Figure represent the 95% confidence intervals associated with the estimated average emissions.

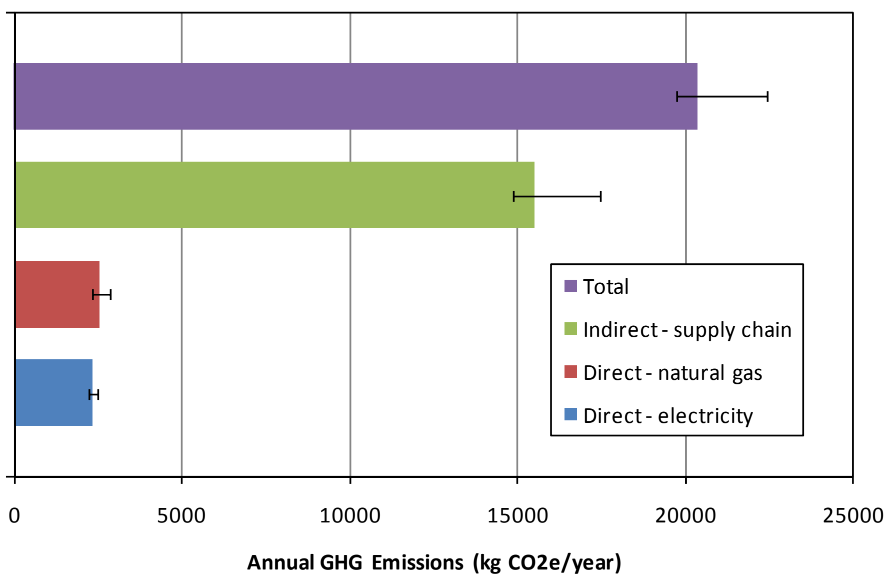

Figure ES-1: Estimated annual direct and supply chain GHG emissions per household

The direct and supply chain emissions estimates were also disaggregated by key residential and supply chain fuel end uses to provide insight into the underlying processes and technologies contributing the carbon footprint of California households. These disaggregated results were further assessed in a case study aimed at quantifying the carbon footprint reductions achievable through the adoption of more energy efficient residential and supply chain technologies. A suite of best practice technology measures applicable to many of the direct and supply chain fuel end uses were characterized and assessed in the modeling framework. The resulting estimates for achievable carbon footprint reduction potentials by measure type are summarized in Figure ES-2 (in this Figure residential measures apply to the GHG emissions resulting from direct home energy use in Figure ES-1, while commercial, industrial, and agricultural measures apply to supply chain GHG emissions in Figure ES-1). The error bars in Figure ES-2 represent the 95% confidence intervals associated with the estimated average emissions.

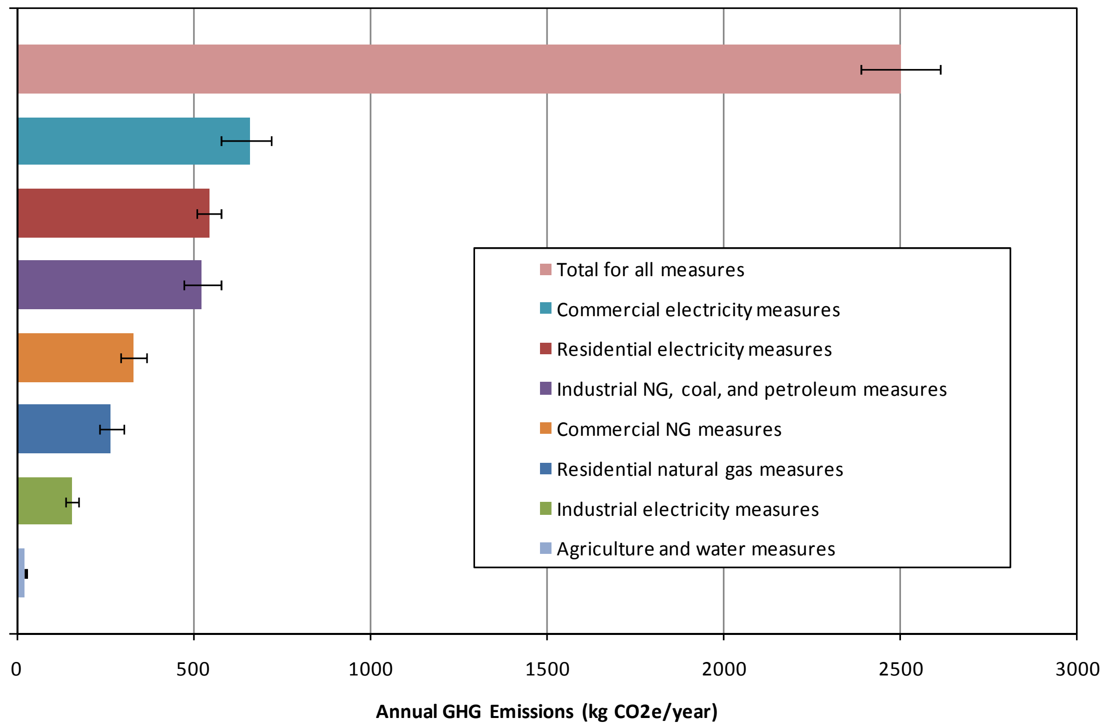

Figure ES-2: Estimated GHG emission reductions per household by measure type

Conclusions

The results of the case study suggest that significant reductions in the average carbon footprint of California households might be realized through the adoption of energy efficient technologies in California dwellings and in the supply chains that produce goods and services purchased by Californians. For the technology measures considered, the GHG emissions reduction potential was estimated at roughly 13% of the case study direct and supply chain carbon footprint.

The preliminary parameter uncertainty assessment conducted in this project revealed significant uncertainties surrounding the average carbon footprint estimates generated by the model. Large confidence intervals in the non-energy supply chain GHG emission factors are particularly important to acknowledge when interpreting the results of this project.

Benefits to California

The results of this project provide two important contributions toward improved California-specific household carbon footprint analysis. First, the direct and supply chain GHG emissions modeling frameworks developed in this project provide greater bottom-up end use detail than existing carbon calculators. This bottom-up detail allows California energy and policy analysts to better understand the underlying technologies and processes contributing to the carbon footprint of California households, and to better assess specific technology improvement options for reducing the household carbon footprints in California.

Second, the preliminary parameter uncertainty assessments conducted in this project provide much needed information on the minimum uncertainty surrounding the model's carbon footprint estimates, which will help California energy and policy analysts better assess the usefulness (and limitations) of these carbon footprint estimates toward policy decisions. The contributions of this project should therefore improve the state of the art in carbon footprint analyses for California, which can help researchers and policy analysts identify strategies for reducing the carbon footprints of California residents with greater confidence.

2.0 Introduction

2.1. Background and Overview

There is growing interest in the development of tools and methods for calculating the "carbon footprint" associated with personal consumption. A carbon footprint is defined as the annual carbon emissions attributable to a given consumption activity, such as personal transportation or the purchase and use of goods and services.

For activities related to physical products such as food items, automobiles, or electronics, a carbon footprint typically includes the carbon emissions arising from raw materials acquisition, product manufacture, product distribution, product use, and product disposal/recycling. For services such as banking, health care, and hair salons, the carbon footprint typically includes the emissions associated with constructing and maintaining the infrastructure necessary to provide that service to the consumer (for example, office buildings, data centers, communications systems, furniture, paper, and supplies).

Carbon footprint estimation leverages an analytical method known as life-cycle assessment (LCA), which is a structured framework for identifying, modeling, and holistically comparing the environmental impacts of complex systems. Ideally, an LCA should include all important environmental impacts. However, LCA-based studies and tools with a singular focus on carbon emissions are becoming increasingly common as society seeks to mitigate the impacts of climate change.

In particular, there has been much recent emphasis on tools and studies related to estimating household carbon footprints. The focus on household consumption is warranted, given that household consumption activities are expected to generate a significant share of global greenhouse gas (GHG) emissions. For example, Weber and Matthews (2008) estimated that the global carbon footprint of U.S. households—including personal transportation, operation of dwellings, and consumption of goods and services—amounted to roughly 5700 megatons (Mt) in 2004.[1]

One outcome of this widespread focus on household carbon footprints has been the introduction of a few dozen carbon footprint calculators over the last two to three years (for a recent review of some available tools, see United Nations (2008)). Most of these tools target the consumer, and are designed to raise awareness of the linkage between personal consumption and global climate change.

In this project, Lawrence Berkeley National Laboratory (LBNL) developed a household carbon footprint modeling framework that should prove more useful to state policy analysis than existing consumer-focused carbon footprint calculators. Specifically, this project utilized a bottom-up modeling approach to estimate the carbon footprints associated with dwelling operation and supply chains for producing goods and services. This bottom-up detail allows energy and policy analysts to better understand the underlying technologies and processes

[1] In comparison, the U.S. national GHG inventory totaled around 7100 Mt in 2004 (U.S. EPA 2008a).

contributing to the carbon footprint of California households. This detail also facilitates the analysis of specific technology improvement options for reducing household carbon footprints in California.

2.2. Project Objectives

The main goal of this project was to develop and demonstrate a household carbon footprint modeling framework that would provide California energy and climate researchers with a more useful tool for analyzing policies aimed at reducing the carbon footprints of state residents.

In support of this goal, the project had three primary objectives: (1) to compile information sufficient to characterize the annual household consumption of energy, goods, and services by California residents; (2) to develop a modeling framework to estimate the carbon footprint associated with these consumption activities; and (3) to analyze some policy-relevant options for reducing the carbon footprints of California residents.

While the research team met each of these project objectives, some key aspects of the analysis differed from the original research plan due to external developments. In 2006 when the original research plan was written, no California-specific carbon footprint tools existed. Thus, the original research plan was designed largely to fill existing voids in data compilation and modeling techniques relevant to state-level carbon footprint analysis.

Since 2006, however, several tools and studies have emerged that provide greater state-specific carbon footprint estimation capabilities. For example, the Cool California carbon footprint calculator (Cool California 2008) –which was released under the auspices of several state agencies –provides estimates based on local utility emission factors.[2] The Cool California calculator also estimates supply chain carbon footprints based on different consumption patterns for energy, goods, and services in California, which can be varied by in-state region of residence and income level. These consumption pattern data are similar to what the research team originally planned to compile to meet objective (1).

Additionally, work sponsored by the California Air Resources Board (CARB) is currently adding California-specific capabilities to the national Economic Input-Output Life-Cycle Assessment (EIO-LCA) model (Hendrickson et al. 2006; CMU 2008). The EIO-LCA model estimates the average supply chain emissions associated with purchases of a wide variety of goods and services. Originally, the research team planned to take a similar, but more preliminary, approach to tailoring national EIO-LCA data to California as part of the research related to objective (2). However, the recent CARB-sponsored work provides state-specific supply chain analysis capabilities that exceed the limited reach of the research team's original approach.

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[2] The Low Impact Living carbon footprint calculator (Low Impact Living 2008) also allows one to tailor results based on regional environmental impact data. However, the research team could not verify the underlying regional data assumptions, and hence the tool's capabilities for providing California-specific analyses.

Thus, the team adjusted its research plan to ensure that the results of this project would still be novel and important contributions to state-specific carbon footprint analysis methods. Specifically, the research team developed a bottom-up supply chain modeling framework that disaggregates the carbon footprint of purchased goods and services by major energy end use (e.g., lighting and motor systems) across the supply chain. These capabilities allow for detailed assessment of supply chain emissions sources and technology-based emissions mitigation potentials, and represent a significant enhancement to existing supply chain carbon footprint methods.

Additionally, the team conducted a preliminary parameter uncertainty assessment of the new modeling framework to aid in interpreting results. Although it is widely accepted that uncertainties are pervasive in carbon footprint assessments, little work has been published to date that attempts to address these uncertainties in a quantitative manner.

Both of these research plan adjustments addressed important knowledge gaps while allowing the research team to meet the original project objectives.

2.3. Report Organization

The report begins with a description of the project approach in Section 3, including the key analytical methods and data sources used to construct bottom-up carbon footprint models related to household energy use and purchased goods and services. Section 4 discusses project outcomes and presents the results of the baseline analysis and preliminary uncertainty assessment. Also presented in Section 4 are the results of a case study to assess the potential for reducing the carbon footprint of a prototypical California household through the deployment of key best practice technologies. Lastly, Section 5 provides conclusions and recommendations.

3.0 Project Approach

3.1. Overview

The carbon footprint modeling framework developed in this project has two primary components: a direct household emissions modeling component and a supply chain emissions modeling component. The direct household emissions model estimates the annual carbon emissions associated with household energy use in California, which is attributable to various end uses for electricity and natural gas (e.g., space heating, appliances, lighting, and entertainment equipment). The supply chain emissions modeling component estimates the annual carbon emissions associated with the purchase of household goods and services.[3]

The modeling framework developed in this project was designed for aggregate-level analyses of household carbon footprints and policy strategies for reducing these footprints. Thus, data compilation efforts focused on information related to the energy use and consumption patterns at the level of the household. However, the modeling framework developed in this study could be used to estimate the carbon footprints of individuals if the appropriate data are available.

The research team also conducted a preliminary analysis of parameter uncertainty associated with the data used to construct and populate the direct and supply chain carbon emissions models. Both modeling components relied extensively on publicly-available data sources and estimates that contained inherent uncertainties. For example, the supply chain modeling framework relied on data from national-level economic and energy use surveys, which are subject to both sampling and non-sampling errors. Where available, the research team compiled information on survey standard errors or other estimation uncertainties associated with the data used to develop the models.

There are two important caveats to the uncertainty assessment conducted in this project. First, the research team only considered parameter uncertainty associated with key data assumptions in the modeling framework. An assessment of modeling uncertainty was beyond the scope of this project.[4] Second, because parameter uncertainty information was not available for all data used to construct the models, only a partial parameter uncertainty assessment was possible. Thus, the uncertainty assessment could only estimate the minimum confidence intervals associated with key modeling results. However, the establishment of minimum confidence

3 This project did not address the carbon emissions associated with personal transportation, given that such analyses are already possible with reasonable accuracy using available carbon calculator tools such as Cool California. However, the carbon emissions associated with household energy use and the purchase of goods and services are estimated to account for around two-thirds of the average household carbon footprint in the United States (Weber and Matthews 2008).

4 Parameter uncertainty refers to the uncertainty associated with model input data. Modeling uncertainty refers to uncertainties introduced by the underlying mathematical structure of a model. Proper assessment of modeling uncertainty typically involves comparing the results of different models to expose how structural differences between models affect results.

intervals is still a valuable contribution given the dearth of information on parameter uncertainty in previous carbon footprint studies and available carbon calculators.

Section 3.1 provides an overview of the key assumptions and data sources used to develop the direct household carbon emissions model. The assumptions and data sources associated with the supply chain emissions model are discussed in Section 3.2. Both sections also provide a summary of the research team's approach for estimating parameter uncertainties in the modeling framework. The limitations of the supply chain modeling approach are discussed briefly in Section 3.3.

3.2. Direct Household Emissions Modeling Framework

Most household carbon footprint models estimate direct emissions based on household-level energy use data, which individuals can obtain from utility bills or household electricity and natural gas utility meters. Such an approach is appropriate for individuals who wish to estimate their total carbon footprint, and to better understand the relative contribution of household energy use to that footprint.

In order to assess state-level policy options for reducing household carbon footprints, however, a more detailed representation of household energy end use technologies is required. Specifically, state energy and policy analysts require bottom-up details that reflect current saturations and efficiencies of key household appliances and dwelling characteristics. Such detail is required to more accurately estimate the household carbon emission reduction potentials associated with behavior- and technology-based mitigation policies.

The basic form of the bottom-up modeling framework that was used to estimate the average direct emissions of California households in this project is expressed in Equation 1.

(1) $$\overline{G}_D = \sum_{i=1} \sum_{j=1} \left(\overline{UEC}_{ij} * s_{ij} * \overline{g}_i \right)$$

Where: $\overline{G}_D$ = average annual direct household GHG emissions (kg CO_2e/year)

$\overline{UEC}_{ij}$ = average unit energy consumption of end use technology j for fuel i (units = kWh/year for electricity and therms[5]/year for natural gas)

s_{ij} = saturation of end use technology j for fuel i (%)

$\overline{g}_i$ = average residential GHG emission factor for fuel i (units = kg CO_2e/kWh for electricity end uses and kgCO_2e/therm for natural gas end uses)

[5] A therm is equivalent to 100,000 British thermal units, or 105.5 megajoules, of energy.

Given California's historical focus on research and standards for residential energy efficiency, sufficient data exist to populate the model described by Equation 1. To do so, the research team used technology unit energy consumption (UEC)[6] and saturation data from the California Residential Appliance Saturation Survey (RASS) database (KEMA 2008).

The RASS database includes estimates of residential technology saturations (as of 2004) based on surveys data from 21, 920 customers of California's main electricity and natural gas utility companies. Saturation data are provided for 28 electricity end use technologies and 7 natural gas end use technologies. The RASS study also provides average UEC values for end use technologies in each survey sample, based on regression analysis of utility billing data using a conditional demand model (KEMA-Xenergy et al. 2004).

Furthermore, the RASS database allows for analysis of technology saturation and UEC data based on household region, utility company, dwelling type, income level, and other household characteristics. In this project, the research team focused on compiling average UEC and technology saturation data across all California households (i.e., a composite of all household types) in the RASS database.

Next, the research team estimated confidence intervals for the RASS technology saturation and average end use UEC data. Ninety-five percent confidence intervals were estimated for each technology saturation assumption, based on survey sampling error estimates provided by KEMA-Xenergy et al. (2004) for the different sample populations in the RASS study. (These sample populations were based on California utility territories and metered versus non-metered households).

The RASS study did not explicitly estimate standard errors for its average end use UEC estimates. However, the regression analysis approach used by the RASS study team to estimate average end use UECs is analytically similar to the regression approach used by the U.S. Department of Energy to estimate end use UECs in its quadrennial U.S. Residential Energy Consumption Survey (RECS) (U.S. DOE 1983). Thus, the research team used published standard errors for average end use UECs from the 2001 RECS (U.S. DOE 2003) as proxies for RASS end use UEC standard errors in this project.

Table 1 and Table 2 summarize the 95% confidence intervals that were estimated for weighted average UECs by end use and fuel for California households.[7] An important caveat is that the confidence intervals in Table 1 and Table 2 refer only to the statistical confidence in the estimates of weighted average UECs in these Tables (i.e., within what range the "true"—i.e., population—weighted average UEC would lie if one could take an infinite number of survey samples from the population). These confidence intervals should not be interpreted as

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[6] Unit energy consumption refers to the annual energy use of a given appliance.

[7] Weighted average UECs were calculated by multiplying the average end use UEC by its saturation across all California households (i.e., the product of the first two variables in the right side of Equation 1). The 95% confidence intervals in Tables 1 and 2 were generated via Monte Carlo analysis (1000 runs) using Crystal Ball software.

capturing 95% of the population distribution of individual household UECs for a particular end use.[8]

Furthermore, the data presented in Table 1 and Table 2 represent the average of all California households; however, the methods described in this section could be employed to generate similar data to estimate direct household carbon emissions for particular segments of the California household population (e.g., by income class, dwelling type, or region of residence).

Table 1: Estimated average electrical end use UECs and 95% confidence intervals

End Use	UEC (kWh/year)	95% Confidence Interval	
		Lower	Upper
Space heating (conventional)	78	64	94
Space heating (heat pump)	12	6	18
Auxiliary space heating	59	49	68
Furnace fan	76	66	88
Central air conditioning	507	387	630
Room air conditioning	31	18	44
Evaporative cooling	25	17	35
Water heating	167	126	214
Dryer	192	175	211
Clothes washer	80	74	86
Dish washer	47	43	51
First refrigerator	789	736	842
Additional refrigerator	212	189	237
Freezer	168	150	188
Pool pump	240	208	274
Spa	37	32	43
Outdoor lighting	143	131	154
Range/oven	110	100	120
Television	466	433	499
Spa electric heat	68	51	86
Microwave	126	117	135
Home office equipment	27	24	30
Personal computer	390	360	420
Water bed	16	9	24
Well pump	34	26	43
Interior lighting and misc.	1832	1703	1960
Total electricity use	**5932**	**5697**	**6172**

[8] Streiner (1996) provides a helpful review of the use of standard errors for constructing confidence intervals from survey data, and their difference from the standard deviation.

Table 2: Estimated natural gas end use UECs and 95% confidence intervals

End Use	UEC (therms/year)	95% Confidence Interval	
		Lower	Upper
Space heating	188	165	211
Water heating	189	163	215
Dryer	13	11	14
Range/oven	31	28	34
Pool heating	7	4	9
Spa heating	4	3	5
Total natural gas use	**431**	**391**	**471**

The research team also estimated average GHG emission factors, and the 95% confidence intervals associated with these estimated average GHG emission factors, for residential electricity and natural gas use in California. These estimates are summarized in Table 3

The GHG emission factor for electricity was based on information from Marnay et al. (2002), which presented fuel data for electricity generation and estimates for average carbon intensity of California electricity (including imported electricity) from three different models. The fuel data from Marnay et al. (2002) were coupled with average GHG emission factors by fuel from the California GHG emissions inventory (CARB 2008).

However, no uncertainty data for the California GHG emissions inventory estimates for electricity generation could be found in the public domain. Thus, the research team estimated 95% uncertainty ranges for electricity generated from different fuel types based on data from the Intergovernmental Panel on Climate Change's (IPPC's) GHG emission factor database (IPCC 2008) and the U.S. national GHG emissions inventory (U.S. EPA 2008a).

The GHG emission factor for residential natural gas combustion in California was based on emission factors obtained from the California GHG emissions inventory (CARB 2008). As for the GHG emission factors for electricity generation, no uncertainty data for the California GHG emissions inventory estimates for natural gas combustion could be found in the public domain. Thus, the research team estimated 95% uncertainty ranges for residential natural gas combustion based on data from the IPPC's GHG emission factor database (IPCC 2008) and the U.S. national GHG emissions inventory (U.S. EPA 2008a).

Table 3: Estimated average GHG emission factors for California household energy use

Emission factor	Unit	Value	95% Confidence Interval	
			Lower	Upper
Electricity	kg CO2e/kWh	0.40	0.38	0.44
Natural gas	kg CO2e/therm	5.92	5.71	6.34

3.3. Supply Chain Emissions Modeling Framework

To estimate the life-cycle emissions generated by the purchase of various household goods and services, the research team relied on an established modeling approach that couples input-output (IO) economic data with sector-level data on energy use and GHG emissions.

Simply described, such models have two primary structural components. The first component is an IO total requirements matrix that quantifies the economic interdependencies of all key sectors in an economy. For a unit of economic output from one sector, the total requirements matrix allows one to estimate the corresponding economic inputs to that sector that are required from all other sectors in the economy. The second component is a set of coefficients that quantify the average fuel use and GHG emissions per unit of economic output for each sector in the economy. By coupling these coefficients with the data in the total requirements matrix, it is possible to estimate the economy-wide energy use and GHG emissions associated with a unit of economic output from any sector in the economy.

This general approach gained traction in the United States in the 1970s in the field of net energy analysis (Herendeen and Bullard 1975). More recent work has extended this approach to include other environmental impact categories (e.g., criteria air pollutants and toxic emissions), most notably by Carnegie Mellon University (CMU) in the development of its widely-used Economic Input-Output Life-Cycle Assessment (EIO-LCA) tool (Hendrickson et al. 2006; CMU 2008).[9]

Additionally, a number of researchers have used the general approach to derive population-level estimates of the carbon footprints associated with a variety of consumer spending activities in different geographic regions. Recent examples of such work include supply chain carbon footprint analyses for the United States by Weber and Matthews (2008), for the state of Washington by Morris et al. (2007), for the Netherlands by Vringer and Blok (1995), for Australia, Brazil, Denmark, India, and Japan by Lenzen et al. (2006), and for Korea by Park and Heo (2007).

The IO-based supply chain modeling framework developed in this project expanded previous work in two important ways. First, the research team developed fuel end use coefficients for many of the economic sectors in its model. An end use is defined as an energy-consuming technology or process within a given sector, such as lighting and heating, ventilation, and air conditioning (HVAC) in the commercial sector or motors and steam systems in the industrial sector. The fuel end use coefficients developed by the research team provide greater detail on

[9] For more information on the IO-based LCA approach, the reader is referred to the references cited in this paragraph.

the nature of energy use and energy-related GHG emissions across the supply chain than previous work provides. Such end use detail also facilitates the assessment of technology-specific supply chain GHG mitigation strategies (see Section 3), which is valuable for policy analysis.

Second, the research team included parameter uncertainty estimates when constructing the supply chain model, whenever such estimates were available. This uncertainty analysis helps shed light on how precisely the modeling framework can estimate average supply chain GHG emissions using available data sources.

The research team used the 2002 U.S. benchmark total requirements matrix to model IO transactions across the supply chain for 426 economic sectors. This matrix was developed by the U.S. Bureau of Economic Analysis (U.S. BEA 2008) and is the most recent benchmark matrix available.[10] Details specific to the estimation of energy coefficients are described in Section 3.3.1. The process for estimating GHG emission coefficients is described in Section 3.3.2.

3.3.1. Supply Chain Fuel Use

The fuel use coefficients developed in this project were based largely on fuel use data that were compiled by CMU in the development of its 2002 U.S. benchmark EIO-LCA model (Weber and Matthews 2009). The research team used the CMU data to construct fuel use coefficients for all 426 sectors in the 2002 benchmark total requirements matrix across five different fuel categories: (1) purchased electricity; (2) natural gas; (3) coal; (4) petroleum; and (5) biomass/wastes/other.

Next, the research team compiled available information to characterize the average fuel end use breakdown for each IO sector for which such data existed.

For the manufacturing IO sectors, which represent 279 of the 426 sectors contained in the total requirements matrix, the research team derived average end use breakdown data for purchased electricity, natural gas, coal, and petroleum using information from the U.S. Department of Energy's 2002 and 1997Manufacturing Energy Consumption Surveys (MECS) (U.S. DOE 2001, 2005). The MECS data were used to disaggregate total IO sector fuel use into 10 distinct end uses, which are summarized in the first section in Table 4.[11]

The MECS provides average U.S. fuel end use breakdown data for 69 different North American Industry Classification System (NAICS) codes (data are available for all 3-digit NAICS codes, and many 4-digit and 6-digit NAICS codes). Where an exact match existed between a manufacturing IO sector and a NAICS code for which MECS end use breakdown data existed, the research team applied the corresponding MECS end use breakdown data. For most IO

[10] The U.S. BEA develops detailed benchmark IO Tables roughly every five years. The previous benchmark IO Table, which contained nearly 500 sectors, was developed for 1997.

[11] MECS end use data are provided for 14 different end use categories in total; the research team combined four of these categories (other process use, other facility support, other nonprocess use, and end use not reported) into one generic "other" category.

sectors, however, the research team had to apply the nearest match, which was at worst the MECS breakdown at the 3-digit NAICS level.

For the commercial IO sectors, the research team developed average fuel end use breakdown data for purchased electricity and natural gas, which are the dominant fuels used in commercial buildings in the United States. These end use breakdown data were derived using information from the U.S. Department of Energy's 2003 Commercial Building Energy Consumption Survey (CBECS) (U.S. DOE 2008a). The CBECS provides average breakdown data for nine separate commercial end uses of electricity, and three separate commercial end uses of natural gas. The commercial end use categories are summarized in the second and third sections in Table 4.

Table 4: Fuel coefficient end use disaggregation for various IO sectors

Manufacturing (electricity, natural gas, coal, and petroleum)	
Conventional Boiler Use	Facility HVAC
CHP and/or Cogeneration Process	Facility Lighting
Process Heating	Onsite Transportation
Process Cooling and Refrigeration	Conventional Electricity Generation
Machine Drive	Other
Electro-Chemical Processes	
Commercial (electricity)	
Space Heating	Cooking
Cooling	Refrigeration
Ventilation	Office Equipment
Water Heating	Computers
Lighting	Other
Commercial (natural gas)	
Space Heating	Cooking
Water Heating	Other
Agriculture (electricity, natural gas, petroleum)	
Motors	Machinery
Lighting	Other
Onsite transport	
Water treatment (electricity)	
Pumping systems	Other

Unlike the MECS, the CBECS does not report fuel end use breakdown data by NAICS code. Rather, all data are reported by building type.[12] However, the U.S. Department of Energy

[12] There are 16 different building types for which data are available in CBECS: education, food sales, food service, inpatient health care, outpatient health care, lodging, retail (other than malls), enclosed and strip malls, office, public assembly, public order and safety, religious worship, service, warehouse and storage, other, and vacant.

provides a rough Table of correspondence between CBECS building types and 3-digit NAICS code (U.S. DOE 2008a). The research team used this Table to first map the CBECS data to NAICS codes, which were then mapped to the appropriate IO sector. This process allowed the research team to estimate electricity and natural gas end use breakdown data for 103 IO sectors.

Lastly, electricity use for water and sewage treatment was disaggregated into pumping versus non-pumping electricity use based on information from Brown et al. (2007).

In total, the above approach allowed the research team to estimate important fuel end uses in 397 of the 426 IO sectors in the 2002 benchmark total requirements matrix.

Equation 2 summarizes the general approach for estimating the total economy-wide energy use, and energy use of key supply chain end uses, associated with a unit of economic output from a given IO sector.

$$\overline{E}_{ijl} = \sum_{k=1}^{n} \left(\overline{e}_{ik} * \overline{f}_{ijk} * o_{kl} \right) \quad (2)$$

Where: $\overline{E}_{ijl}$ = average use of fuel i for end use j per unit of output from sector l (MJ/$)

n = number of sectors in the IO matrix

$\overline{e}_{ik}$ = average use of fuel i per unit output from sector k (MJ/$)

$\overline{f}_{ijk}$ = average fraction of total energy from fuel i that is needed for end use j in sector k (%)

o_{kl} = total dollar output required from sector k to produce a dollar of output from sector l

The research team also compiled parameter uncertainty information for data used to construct the fuel and fuel end use coefficients, when such uncertainty information existed. For the fuel coefficients (i.e., the variable $\overline{e}_{ik}$ in Equation 2), the team constructed 95% confidence intervals for the following fuels and IO sectors:

- all fuels for the manufacturing IO sectors, based on survey standard error data from the 2002 MECS (U.S. DOE 2005)
- electricity and petroleum use for the construction IO sectors, based on survey standard error data from the 2002 U.S. Economic Census (U.S. Census Bureau 2005).

For the fuel end use breakdown fractions (i.e., variable $\overline{f}_{ijk}$ in Equation 2), the research team constructed 95% confidence intervals for the following fuel end uses and IO sectors:

- all fuel end uses in the manufacturing IO sectors, based on survey standard error data from the 2002 MECS (U.S. DOE 2005)
- all fuel end uses in the commercial IO sectors, based on survey standard error data from the 2003 CBECS (U.S. DOE 2008a).

As in the previous section, the 95% confidence intervals referred to the statistical confidence in the estimates of average fuel use by IO sector (i.e., within what range the "true"—i.e., population—average fuel use per sector would lie if one could take an infinite number of survey samples from the population). The confidence intervals were not meant to capture 95% of the population distribution of fuel use at individual establishments within an IO sector.

3.3.2. Supply Chain GHG Emissions

Equation 3 summarizes the general approach for estimating the total economy-wide GHG emissions associated with a unit of economic output from a given IO sector. The research team estimated supply chain GHG emissions arising from fossil fuel use (i.e., the first term on the right side of Equation 3) as well as supply chain GHG emissions arising from non-energy sources in (i.e., the second term on the right side of Equation 3).

$$\overline{G}_l = \sum_{i=1} \sum_{j=1} \left(\overline{E}_{ijl} * \overline{g}_i^F \right) + \sum_{k=1}^{n} \left(o_{kl} * \overline{g}_k^P \right) \qquad (3)$$

Where: $\overline{G}_l$ = average economy-wide GHG emissions generated per unit output from sector l (kg CO_2e/$)

$\overline{E}_{ijl}$ = average use of fuel i for end use j per unit of output from sector l (MJ/$)

$\overline{g}_i^F$ = average GHG emission factor for fuel i (kg CO_2e/MJ)

o_{kl} = total dollar output required from sector k to produce a dollar of output from sector l

$\overline{g}_k^P$ = average process (i.e., non-energy) GHG emissions per unit output from sector k (kg CO_2e/$)

Supply chain GHG emissions arising from fossil fuel use were estimated using an average GHG emission factor for each fuel. These emission factors were multiplied by average supply chain fuel use (as estimated by the process described in Section 2.3.1) to arrive at an estimate of average supply chain fuel-related GHG emissions. The research team estimated average GHG emission factors for each fuel type based on data from the IPPC's GHG emission factor database (IPCC 2008) and the U.S. national GHG emissions inventory (U.S. EPA 2008a).

Table 5 summarizes the assumed average value and 95% confidence interval for each fossil fuel emission factor. The large parameter uncertainty surrounding the average emission factor for waste and other fuels reflects the diversity of possible fuels that fall into this category; however, with improved data on waste and other fuels used by IO sector this parameter uncertainty can be reduced.

Table 5: Estimated average GHG emission factors for supply chain fuel use

Fuel	kg CO2e/MJ	95% Confidence Interval	
		Lower	Upper
Natural gas	0.056	0.054	0.058
Coal	0.098	0.095	0.101
Liquefied petroleum gas	0.069	0.068	0.073
Motor Gasoline	0.074	0.073	0.075
Distillate Fuel	0.072	0.071	0.074
Residual Oil	0.077	0.076	0.079
Waste and other fuels	0.116	0.048	0.183

Non-energy sources of GHG emissions in the supply chain include such sources as landfill methane emissions, agricultural soil and manure management, enteric fermentation (i.e., methane from animals), fugitive emissions from fossil fuel production and distribution, and process-related emissions from steel, cement, and semiconductor manufacture. To estimate these emissions, the research team relied on IO sector level non-energy GHG emission data compiled by CMU in the development of its 2002 U.S. benchmark EIO-LCA model (Weber and Matthews 2009). The primary source for the CMU data was the 2002 U.S. national GHG emissions inventory from the U.S. Environmental Protection Agency (U.S. EPA 2004).

The U.S. EPA (2004) national inventory contains estimates of non-energy related GHG emissions from over forty different sources, along with 95% confidence intervals for each estimate. The estimated confidence intervals for many of these data are significant; for example, the range for methane emissions from landfills is +/-30%, the range for methane emissions from natural gas systems is +/-40%, and the range for process-related CO_2 emissions from iron and steel production is +78%/-58%. Such uncertainties are currently unavoidable given the state of measurement and estimation techniques for these GHG inventory data; however, they also represent important parameter uncertainties in the modeling framework of this study.

To construct 95% confidence intervals for non-energy GHG emissions in the supply chain model, the research team first compiled 95% confidence interval estimates from U.S. EPA (2004) for each important emissions source. Next, the research team mapped these uncertainties to IO sector-level non-energy GHG emission coefficients using the CMU 2002 EIO-LCA data.

3.3.3. Limitations

The general IO-based approach used for supply chain modeling in this project has several benefits, including the ability to model complex life-cycle systems in simple and efficient manner and the ability to estimate average life-cycle impacts for a wide variety of different product groups and types of services.

However, there are a number of key limitations to this method, which have been discussed extensively in the literature (see for example Hendrickson et al. 2006). In particular, there are several limitations that are important caveats to the modeling approach described in Section 3.3.2.

First, the IO benchmark total requirements data used to estimate economy-wide transactions reflect U.S. economic infrastructures and supply chain technologies as of 2002. These are the most recent such IO data available, however, and were first issued by the U.S. Bureau of Economic Analysis in late 2008. The implication is that the supply chain modeling framework developed in this project reflects static transactions that may lose relevance to current supply chains over time.

Second, the method is only capable of estimating average fuel use and GHG emissions for a given IO sector as a whole. For IO sectors with heterogeneous product outputs (e.g., the frozen food IO sector), the method provides fuel use and GHG emissions estimates that are averaged across all goods or services produced by that IO sector. However, the method cannot estimate fuel use and GHG emissions specific to any product within that IO sector (e.g., frozen blueberries).

Third, the method relies on many different data from a diversity of different sources. Thus, the uncertainties associated with the method are significant. However, the preliminary parameter uncertainty estimates compiled in this project provide at least some idea of the minimum parameter uncertainty associated with the estimated averages for each IO sector. This project could not identify parameter uncertainty data for many of the model inputs, though, so the results should not be interpreted as comprehensive of all parameter uncertainties. Additionally, this project did not address modeling uncertainty, which is another key source of uncertainty inherent in the IO-based method.

Moreover, it was not possible to perform a parameter uncertainty assessment of the IO benchmark total requirement matrix, which is the primary structural component of the supply chain modeling framework. Several researchers have explored error propagation in IO Tables in a theoretical fashion (see for example Hendrickson et al 2006, Nijkamp et al. 1992, or Bullard and Sebald 1977). However, given the dozens of data sources used to construct the IO matrices and the lack of publicly available information on data and modeling assumptions, a parameter uncertainty assessment of U.S. IO matrices is not possible. Thus, the parameter uncertainty estimates in this project were limited to available data on fuel use, fuel end uses, and GHG emission factors.

Lastly, the fuel use, fuel end use, and GHG emissions coefficients employed in this study are based on average U.S. conditions for each IO sector. In reality, the supply chains for goods and services consumed in California extend across the globe. There is a growing research effort aimed at developing multi-regional input-output (MRIO) models to disaggregate U.S. supply chain transactions by country of origin (see for example Weber and Matthews 2008). The development of such MRIO models is a complicated process that was beyond the scope of this project. Thus, a limiting feature of the modeling framework discussed in Section 3.3.2 is that all estimates reflect "made in the U.S.A" conditions when in fact global supply chains are required.[13]

As a result, the modeling framework will only provide an average U.S. supply chain footprint when in fact the supply chains for certain goods and services purchased by Californians may differ significantly from national average supply chains. Further implications of this limitation are that the model may overestimate the supply chain GHG emissions—and GHG emission reduction potentials (see Section 4)—for California supply chains, given that California's commercial and industrial buildings are typically more energy efficient than the national average. However, without an MRIO model that disaggregates supply chain fuel use and GHG emissions by activities occurring inside and outside the state, it is difficult to quantify the extent of such overestimation.

[13] Weber and Matthews (2008) estimated that roughly 30% of the supply chain GHG emissions associated with the purchase of goods and services by U.S. households occurs outside U.S. borders. In the future, the modeling framework developed in this project could be coupled with MRIO models (such as those discussed in Weber and Matthews 2008) to estimate supply chain GHG emissions, and GHG emissions reduction potentials (see Section 4) in a more accurate, country-specific fashion.

4.0 Project Results

The main goal of this project was to develop and demonstrate a household carbon footprint modeling framework that would provide California energy and climate researchers with a more useful tool for analyzing policies aimed at reducing the carbon footprints of state residents.

In support of this goal, the research team developed the modeling framework described in Section 3, which can be used to estimate the direct and supply chain carbon footprints of California households in a bottom-up fashion. Furthermore, the research team compiled data to analyze the parameter uncertainty associated with this modeling approach, to the extent feasible.

This section describes how the modeling framework was applied to meet the specific objectives of this project: (1) to estimate the carbon footprint of California households based on representative annual consumption of energy, goods, and services by California residents, and (2) to analyze policy-relevant options for reducing the carbon footprints of California residents.

4.1. Estimation of Home Energy and Supply Chain Carbon Footprints

As discussed in Sections 2 and 3, the research team focused on compiling input data and uncertainty information sufficient to estimate the direct (home energy) of California households as well as the supply chain carbon footprints associated with household purchases. The direct carbon footprint for the average California household was estimated using the analytical approach, data sources, and uncertainty ranges discussed in Section 3.2.

To estimate an average annual supply chain carbon footprint, the research team coupled the modeling framework discussed in Section 3.3 with a prototypical annual portfolio of purchased goods and services based on the U.S. Bureau of Labor Statistics' Consumer Expenditure Survey (CES) (U.S. BLS 2008). The CES compiles data on average U.S. consumer spending for hundreds of different goods and services based on a combination of weekly diaries and quarterly telephone interviews. The CES is a national survey, but also reports spending data at a less detailed level for specific regions and metropolitan areas in the United States.

The research team used 2002 average annual spending data for U.S. households as a proxy for the annual purchases of goods and services in California. These data are summarized in Appendix A. These 2002 national average data were selected for several important reasons.

First, the CES only provides standard survey error estimates for spending data that are reported at the national level. This is because the statistical methods of the survey are designed to characterize national, rather than local, spending habits with reasonable certainty. Thus the research team used national data as a proxy for California in order to estimate the minimum parameter uncertainties of the modeling framework (which was a key goal of this project). The use of regional or metropolitan area CES data are expected to result in greater parameter uncertainties given the survey design.

Second, the IO-based supply chain model reflects national average producer prices. Thus, regional and metropolitan area spending data from the CES (which are reported in local prices) first have to be adjusted for regional differences in the price of goods and services to be fully compatible with the national IO model. The research team could not find sufficient information to convert the regional or California metropolitan area CES data into national average prices for all goods and services.

Third, spending data on goods and services are available in greater detail at the national level then they are at the regional or metropolitan level.

Fourth, although more recent (i.e., 2007) national average data are available from the CES, these data would first have to be converted into 2002 producer prices to be compatible with the 2002 IO model. As a matter of efficiency, the research team chose to use the 2002 CES spending data since they are temporally compatible with the supply chain modeling framework in their current form.

Lastly, the primary goal of this project was to develop improved analytical methodologies for analyzing household carbon footprints, as opposed to developing incrementally better input data for generating California household footprint estimates. Thus, the research team chose the U.S. national CES data as the most appropriate data for illustrating the capabilities of the modeling framework via the case study presented in this section (based on the points made in the preceding paragraphs). However, in the future improved consumer spending data could be developed for California to generate more representative supply chain carbon footprint estimates.

The research team converted the 2002 national average CES data into 2002 national average producer prices using information from the U.S. Bureau of Economic Analysis that estimates post-producer transportation costs and wholesale and retail margins (U.S. BEA 2008). Next, the CES data for each purchased good and service were mapped to the appropriate IO sector (i.e., the economic sector that produces that good or service).

The research team also estimated a 95% confidence intervals corresponding to the average spending data for each purchased good and service using standard error estimates provided by the CES for annual and weekly expenditures (U.S. BLS 2008). The aggregate expenditures associated with each IO sector were then calculated, and each IO sector was lumped into a broader consumption category (e.g., food and beverages consumed at home) to aid in results interpretation using categories proposed by Weber and Matthews (2008) as a guide.

The final assumptions for annual average expenditures (in 2002 producer prices), 95% confidence intervals associated with the average expenditure data, IO sectors, and broad consumption categories are summarized in Appendix A.[14]

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[14] As mentioned in Section 3, this project did not consider the carbon footprint associated with personal transportation. Thus, the annual expenditure assumptions summarized in Appendix A do not include purchases of vehicles (new or used), vehicle-related expenditures (e.g., auto insurance, gasoline, or repair/maintenance), or other transportation-related spending (e.g., airfares).

The good and services spending data in Appendix A were then coupled with the total supply chain GHG emissions estimates for each sector (i.e., kg CO_2e/$) as calculated by the methods summarized by Equations 2 and 3.

Figure 1 summarizes the resulting estimates of the average annual household direct (home energy) and supply chain carbon footprints. Total combined GHG emissions are estimated at roughly 20,000 kg of carbon dioxide equivalent (CO_2e) per year. Of this amount, over three-quarters 15,500 kg of GHG emissions are estimated to be attributable to the consumption of goods and services.

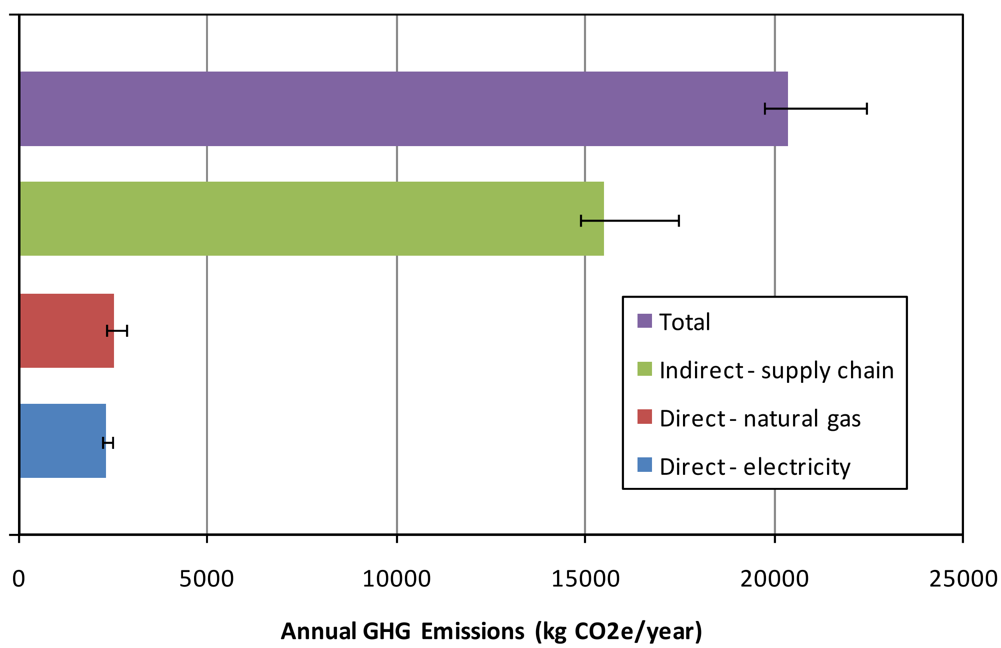

Figure 1: Estimated average annual direct and supply chain GHG emissions per household

The results in Figure 1 suggest that, on average, the carbon footprint associated with household consumption of goods and services is around three times the carbon footprint associated with its home energy use. These results differ significantly from the most recent U.S. average carbon footprint study by Weber and Matthews (2008), which estimated that GHG emissions associated with home utility use were of roughly similar magnitude to supply chain GHG emissions. The disproportionately low contribution of home energy use to California's average household carbon footprint is likely attributable to California's longtime efficiency standards for appliances and residential dwellings, the low carbon intensity of its electricity supply, long running utility and local government programs on energy efficiency, and mild climate.

Also included in Figure 1 are estimated 95% confidence intervals surrounding the reported average values for each results category. These confidence intervals (and all others reported in this section) were estimated via Monte Carlo analysis (1000 runs) using the uncertainty data summarized in Section 3.2 and Equation 1. Crystal Ball software was used for the Monte Carlo analysis.

As mentioned in Section 3, the research team was able to estimate parameter uncertainty information for several key sources of modeling input data, but only for a fraction of the total data inputs. Figure 1 shows that even a partial parameter uncertainty assessment reveals appreciable uncertainty in the estimated average value for total supply chain GHG emissions (+14%/-5%). The uncertainty ranges surrounding the average emissions from home natural gas and electricity use are somewhat smaller, due to relatively lower parameter uncertainties on the appliance energy use, saturations, and residential GHG emission factor input data.

Figure 2 summarizes the estimated average end use breakdown of GHG emissions arising from home natural gas use in California. The majority of GHG emissions associated with household natural gas use is attributable to two primary end uses: water heating and space heating. The estimated 95% confidence intervals surrounding the reported average values for both of these end uses was around +/-15%, which underscores the appreciable uncertainties associated with estimating end use GHG emissions of discrete end uses. Still, this end use resolution provides important capabilities for modeling and assessing carbon footprint reduction strategies, as illustrated in the case study in Section 4.2. Furthermore, the estimated confidence intervals allow the analyst to interpret the results of any further analyses that employ these average end use estimates with the proper level of caution.

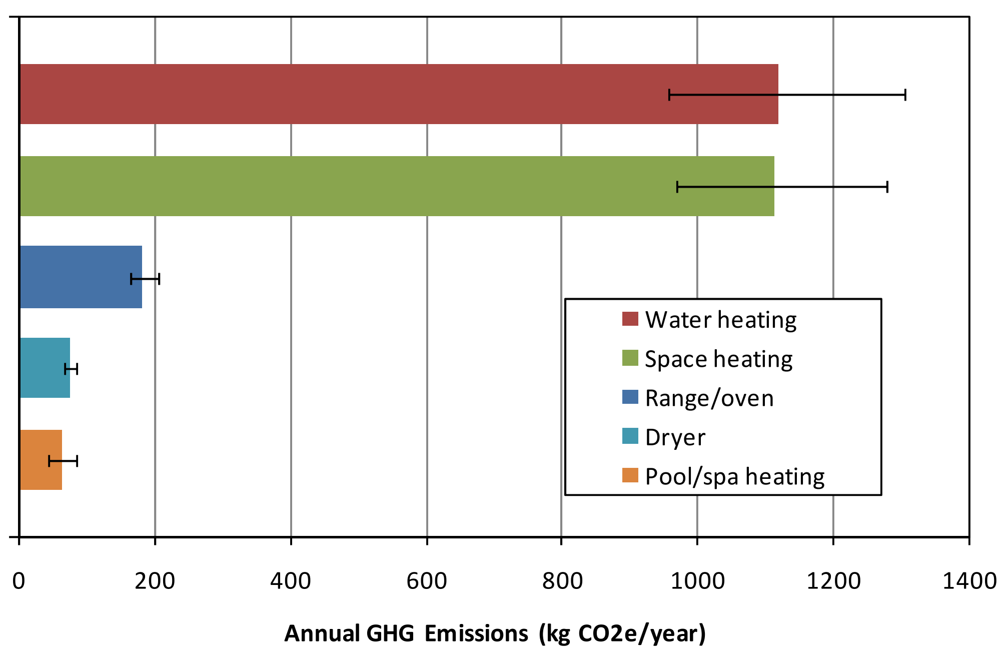

Figure 2: Estimated annual direct natural gas GHG emissions per household by end use

Figure 3 summarizes the estimated average end use breakdown of GHG emissions arising from home electricity use in California. The largest sources of electricity-based GHG emissions in the average California household are seen to be indoor lighting, refrigeration, central air conditioning, televisions, and personal computers. The estimated 95% confidence intervals surrounding the reported averages range from +/-25% for central air conditioning to +/-10% for televisions, lighting, and personal computers.

The results in Figure 2 and Figure 3 are in general agreement with the findings of other recent household energy use studies in California (see for example Itron and KEMA 2008). However, the research contributions of the direct home energy analysis in this project are: (1) the incorporation of available bottom-up end use modeling details into an integrated carbon footprint estimation framework as described in Section 3, and (2) the inclusion of parameter uncertainty analysis to aid in results interpretation. These two contributions can allow state energy and policy analysts to leverage the results of recent household energy use studies in state-specific carbon footprint analyses moving forward.

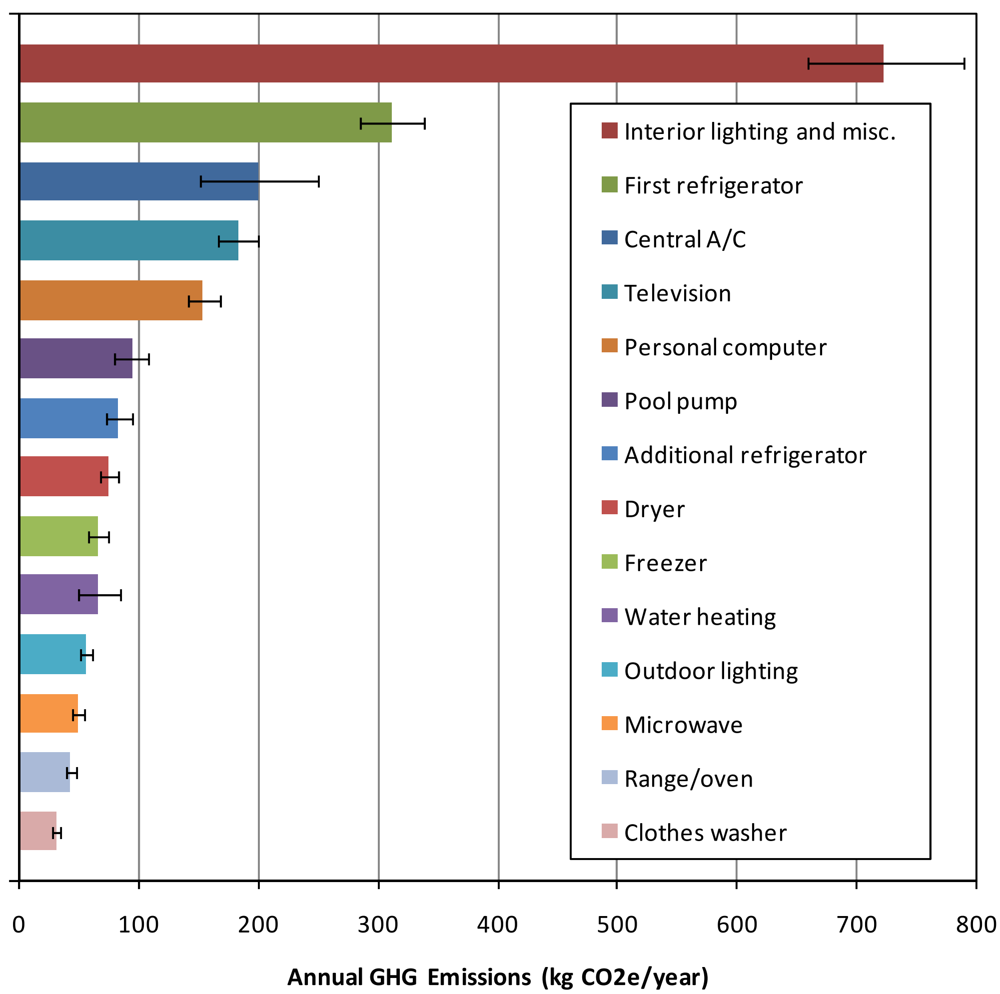

Figure 3: Estimated annual direct electricity GHG emissions by end use

Estimated annual supply chain GHG emissions attributable to the purchase of household goods and services are summarized in Figure 4. The results are presented by key consumption category. The two largest contributors to the supply chain carbon footprint of households are seen to be food and beverages consumed at home, and the broad category of miscellaneous goods and services. This latter category summarizes purchases not related to the other consumption categories and includes a diversity of items such as property taxes, luggage, clocks, lawn and garden supplies, and pet food. Household services (which include water, sewage, and waste collection), restaurants and hotels, household furniture and appliances, and education are also seen to be significant contributors to the supply chain carbon footprint.

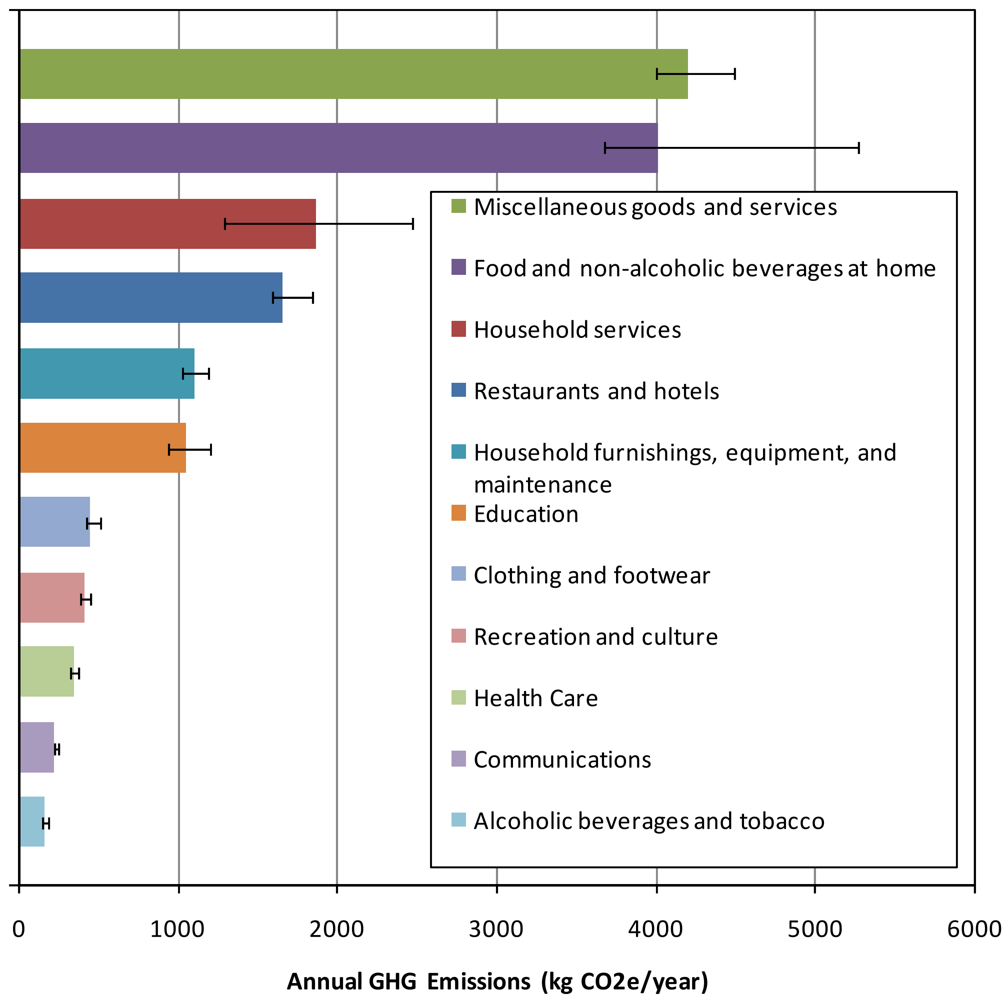

Figure 4: Estimated annual supply chain GHG emissions per household by major consumption category

Figure 4 also suggests that the identified parameter uncertainty surrounding the average results generated for the food and beverages at home (+30%/-10%) and household services (+/-30%) categories are fairly substantial. The major source of identified parameter uncertainty for both of these consumption categories were found to be the non-energy GHG emission factor assumptions in Equation 3, specifically the U.S. EPA (2004) GHG estimates for agricultural soil management and enteric fermentation (important for food items) and for landfills and water treatment (important for household services).

The net effects of parameter uncertainty for non-energy GHG emission factors in the supply chain model are underscored in Figure 5, which summarizes the average supply chain GHG emissions estimates by emissions source. Of the total annual household supply chain GHG emissions (15,500 kg), roughly two-thirds (9,900 kg) are estimated to come from fossil fuel sources and one-third (5,600 kg) are estimated to come from non-energy related GHG emission sources. However, the majority of the identified parameter uncertainty in the supply chain GHG emissions estimate is attributable to the non-energy GHG emission factor data. This parameter uncertainty is currently unavoidable given the state of measurement and estimation techniques related to the U.S. national GHG emissions inventory. However, the results in Figure 4 and Figure 5 suggest that, nevertheless, these parameter uncertainties must be acknowledged when interpreting the results of the IO-based supply chain modeling framework developed in this project.

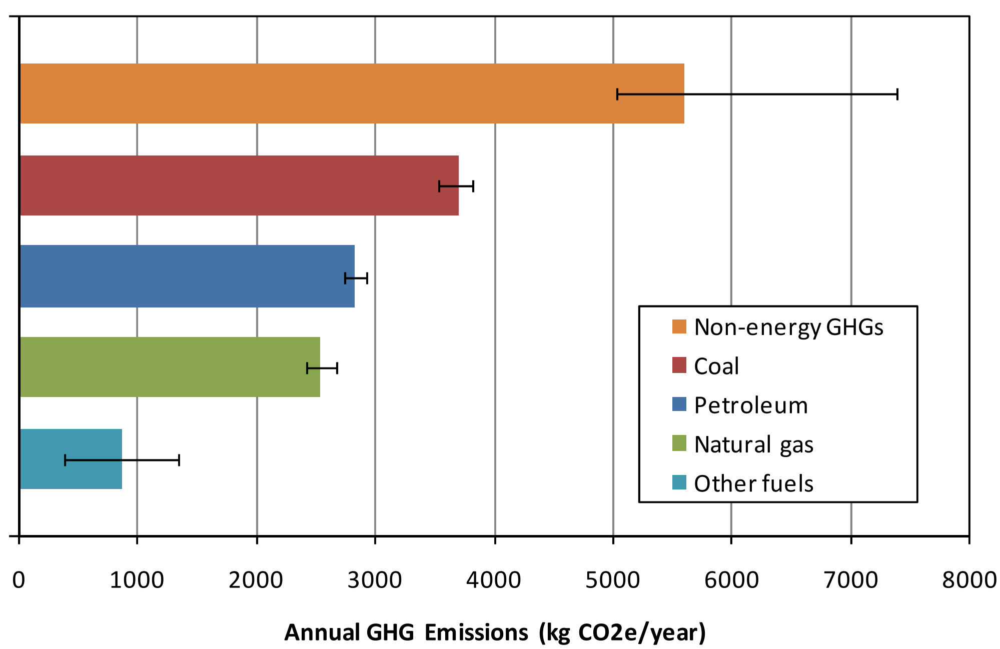

Figure 5: Estimated annual supply chain GHG emissions per household by source category

The results in Figure 4 and Figure 5 agree favorably with the results of similar studies and tools, such as the U.S. national carbon footprint study (Weber and Matthews 2008) and the Cool California calculator (Cool California 2008) (which relies on the EIO-LCA model (CMU 2008) for its supply chain GHG emissions estimates). However, the partial parameter uncertainty estimates facilitated by the supply chain modeling framework developed in this project provide new insights into the nature and significance of the parameter uncertainties that can be quantified by available data. These insights can lead to more informed decision making by state energy and policy analysts.

The most novel feature of the supply chain modeling framework developed in this project, however, is its ability to disaggregate, in a preliminary fashion, energy related supply chain GHG emissions by fuel end use as described in Section 3.3.

Table 6 through Table 9 summarize estimated average supply chain GHG emissions attributable to electricity, natural gas, coal, and petroleum for key fuel end uses in the manufacturing, commercial, agricultural, water treatment, transportation, and power sectors.

As discussed in Section 3.2.3, an important caveat associated with all of these end use GHG emissions estimates is that they are based on average U.S. end use breakdown data, whereas the supply chains for many goods and services included in the model are global in nature. However, these end use data can serve as an important first approximation toward more regionally-accurate MRIO-based models in the future.

Also provided in Table 6 through Table 9 are estimated 95% confidence intervals, which apply to the average annual supply chain GHG emissions estimate for each end use. Based on the parameter uncertainty ranges that could be estimated for key data inputs to the model, the research team estimated 95% confidence intervals that averaged around +/-15% for most fuel end uses. Thus, there are appreciable uncertainties associated with estimating the supply chain GHG emissions at the level of discrete fuel end uses. These uncertainties must be taken into account when interpreting the results of the supply chain modeling framework.

The results in suggest that supply chain electricity use accounts for around one-quarter of the average supply chain GHG emissions footprint of California residents. The end use summary suggests that the vast majority of these electricity related emissions (87%) are attributable to end uses in the manufacturing and commercial sectors.

Moreover, roughly two-thirds of electricity related emissions are estimated to be attributable to three broad end uses: motor systems, lighting, and HVAC systems. Thus, it is likely that these end uses represent important efficiency opportunities for reducing the supply chain GHG emissions footprint of California households. Furthermore, analysis of suggests that around 80% of all supply chain electricity related GHG emissions could be characterized into meaningful end uses (i.e., not generic “other” categories).

Table 6: Estimated annual supply chain electricity related GHG emissions per household by end use

Sector	End Use	kg CO2e/year	% of Total	95% C.I.	
				Lower	Upper
Manufacturing	Machine Drives	751	20%	651	850
	Process Heating	147	4%	1	168
	Process Cooling and Refrigeration	130	3%	108	151
	Facility HVAC	127	3%	108	145
	Electro-Chemical Processes	114	3%	101	127
	Facility Lighting	99	3%	88	110
	End Use Not Reported	52	1%	39	65
	Other Facility Support/Uses	41	1%	35	48
Commercial	Lighting	606	16%	533	685
	Cooling	268	7%	231	304
	Ventilation	251	7%	216	289
	Refrigeration	206	5%	161	256
	Other	200	5%	174	226
	Computers	111	3%	97	125
	Space Heating	80	2%	68	91
	Office Equipment	42	1%	37	47
	Water Heating	40	1%	35	45
	Cooking	28	1%	25	31
Agricultural	Other	259	7%	228	287
	Motors	33	1%	29	36
	Lighting	15	0%	13	16
	Machinery	7	0%	6	8
Water treatment	Motor systems (pumps)	8	0%	7	9
	Other	1	0%	1	1
Unclassified	Unclassified	165	4%	146	184
Total for all sectors		**3782**	**100%**	**3348**	**4192**

Table 7 summarizes the end use estimates for average natural gas related GHG emissions by supply chain end use. It was estimated that process heating, HVAC, and steam system end uses account around one-half of natural gas related emissions. Combined, the manufacturing, commercial, and power sectors account for around 90% of natural gas related GHG emissions.

Table 7: Estimated annual supply chain natural gas related GHG emissions per household by end use

Sector	End Use	kg CO2e/year	% of Total	95% C.I.	
				Lower	Upper
Manufacturing	Process Heating	411	16%	387	441
	Conventional Boiler Use	253	10%	230	284
	CHP and/or Cogeneration Process	134	5%	128	142
	Facility HVAC	59	2%	54	63
	End Use Not Reported	22	1%	18	26
	Machine Drive-Total	21	1%	20	23
	Conventional Electricity Generation	10	0%	10	11
	Other Process Use	9	0%	8	10
	Process Cooling and Refrigeration	8	0%	7	9
	Other Facility Support	7	0%	6	8
Commercial	Space Heating	637	25%	567	717
	Water Heating	83	3%	75	94
	Other	61	2%	59	65
	Cooking	43	2%	36	51
Power	Electricity generation	526	21%	507	549
Unclassified	Unclassified	251	10%	242	261
Total for all sectors		**2537**	**100%**	**2420**	**2675**

Table 8 summarizes the end use breakdown of coal related supply chain GHG emissions estimated by the modeling framework. Electrical power generation accounts for the greatest share of coal related emissions, followed by process heating, cogeneration, and steam systems in the manufacturing sectors.

Table 8: Estimated annual supply chain coal related GHG emissions per household by end use

Sector	End Use	kg CO2e/year	% of Total	95% C.I.	
				Lower	Upper
Manufacturing	Process Heating	184	5%	159	208
	CHP and/or Cogeneration Process	181	5%	159	202
	Conventional Boiler Use	86	2%	76	95
	Other	55	1%	47	62
Power	Electricity generation	3150	85%	3020	3254
Unclassified	Unclassified	38	1%	34	41
Total for all sectors		**3696**	**100%**	**3534**	**3819**

Lastly, the end use breakdown of petroleum related supply chain GHG emissions is summarized in Table 9. Due to lack of comprehensive end use data on supply chain petroleum use, a large percentage of the results (around 60%) fell into the generic "other" or unclassified end use categories. Still, the remaining 40% of petroleum related emissions was associated with known end uses, which sheds partial light on the nature of supply chain petroleum emissions and aids in assessing how those emissions could be reduced by supply chain technology improvements.

Table 9: Estimated annual supply chain petroleum related GHG emissions per household by end use

Sector	End Use	kg CO2e/year	% of Total	95% C.I.	
				Lower	Upper
Manufacturing	Process Heating	132	5%	118	149
	Conventional Boiler Use	102	4%	86	120
	Other	85	3%	64	107
	CHP and/or Cogeneration Process	55	2%	49	63
	Onsite Transportation	51	2%	46	57
Agricultural	Other	188	7%	184	195
	Motors	73	3%	71	76
	Machinery	40	1%	39	41
	Onsite transport	7	0%	7	8
	Lighting	1	0%	1	1
Transportation	Truck	325	12%	318	336
	Air	164	6%	160	170
	Other	109	4%	106	113
	Rail	65	2%	63	67
	Water	54	2%	53	57
Mining and Construction	Unclassified	256	9%	246	270
Power	Central electrical power generation	106	4%	104	110
Unclassified	Unclassified	1000	36%	973	1037
Total for all sectors		**2815**	**100%**	**2745**	**2926**

In total, the bottom-up modeling results summarized in Table 6 through Table 9 attributed roughly two-thirds of the estimated fossil fuel related supply chain GHG emissions to known end uses (i.e., one-third of emissions fell into the generic "other" or unclassified end uses).

4.2. Analysis of Energy Efficient Technology Potentials

Section 4.1 demonstrated the capabilities of the bottom-up GHG emissions modeling framework developed in this project by summarizing estimates of the annual average direct (home energy) and supply chain carbon footprints per household. This section illustrates the policy relevance of this bottom-up approach via a case study that explores how the average household carbon footprint could be reduced through the deployment of best practice energy efficient technologies.

The promotion and deployment of such energy efficient technologies has long been a policy focus in California. Policy mechanisms for increasing the adoption of residential technologies include appliance efficiency standards, equipment rebates and tax incentives, and initiatives aimed at raising awareness. Policy measures for increasing the adoption of efficient supply chain technologies include government green purchasing programs that give preferential treatment to suppliers who demonstrate best practice energy efficiency (for example, demonstrated by ENERGY STAR certification of commercial and industrial buildings) and product carbon footprint labels and standards. The latter policy measure has received much attention in recent years as a market based mechanism to drive superior supply chain performance, with a notable example being the Carbon Trust's Carbon Reduction Label (Carbon Trust 2008).

The end use details included in bottom-up GHG emissions modeling framework developed in this project can allow state energy and policy researchers to model technology deployment scenarios in a direct fashion that is not possible in existing carbon footprint calculator tools.

In this case study, the research team treated the results summarized in Section 4.1 as the current average baseline household GHG emissions. Next, the research team compiled data on energy efficient technology measures applicable to many of the direct and supply chain fuel end uses that were characterized by the bottom-up modeling approach. In particular, this data compilation effort focused on estimating the end use fuel savings achievable in a technical sense through the adoption of a particular efficiency measure, regardless of the cost of that measure. Finally, the team applied the energy savings estimates to each fuel end use in the modeling framework and compared the results to the carbon footprint baseline to calculate GHG emission reduction potentials.

The case study considered key fuel end use efficiency measures applicable to home energy, commercial sector electricity and natural gas, industrial sector electricity, natural gas, coal, and petroleum, agricultural electricity and petroleum, and water treatment electricity. As such, the research team's analysis addressed fuel end uses responsible for a large fraction of the average California household carbon footprint. However, there are undoubtedly many more energy efficient technology measures applicable to these and other IO sectors that were not addressed in this case study (e.g., transportation, mining, construction, and the energy industries). These measures could be included in future work.

Furthermore, the research team did not consider changes to behavior (e.g., turning off lights or purchasing fewer goods), changes to energy supply (e.g., installation of solar photovoltaic panels), non-energy GHG emission mitigation measures (e.g., reductions in landfill gas flaring), or changes to purchased products (e.g., buying recycled paper) in its case study. These are all clearly very important options for reducing one's carbon footprint, which could be explored in the modeling framework in future work. Table 10 summarizes the measures applicable to residential energy efficiency in California dwellings that were considered in this case study.

Many of the savings estimates for each measure reflect best available information on the remaining efficiency potential in California, based on recent efficiency potential studies and analyses of the California residential sector (North 2008; Itron and KEMA 2008). In particular, the Itron and KEMA (2008) study based its estimates in part on RASS data, which helped ensure the consistency of those estimates with the direct GHG emissions baseline in this study. For other measures, savings estimates at the U.S. national were used as they reflected best available information for a given residential end use. In total, the research team considered 12 energy efficient technology measures for household electricity use, and 3 energy efficient technology measures for household natural gas use.

Table 10: Residential technology measure assumptions

End Use	Technology Measure	Savings	Source(s)
Electricity			
Central A/C	Upgrade to SEER=15 split system	13%	North (2008); Itron and KEMA (2008)
Clothes washer	Horizontal axis with improved motor	50%	Brown et al. (2008)
Dishwasher	Upgrade to ENERGY STAR (EF =0.58)	15%	RLW Analytics (2008); North (2008)
First refrigerator	Upgrade to ENERGY STAR	15%	North (2008); Itron and KEMA (2008); U.S. EPA (2008b)
Freezer	Upgrade to ENERGY STAR	15%	North (2008); Itron and KEMA (2008); U.S. EPA (2008b)
Furnace fan	High efficiency motor	25%	Brown et al. (2008)
Interior lighting	Compact fluorescent bulbs	50%	North (2008); Itron and KEMA (2008); Brown et al. (2008)
Personal computer	Energy Star PCs and power management	50%	Brown et al. (2008)
Pool pump	Two-speed pool pump	49%	North (2008)
Second refrigerator	Use first refrigerator to replace second	33%	KEMA (2008)
Television	Reduced standby power losses	25%	Brown et al. (2008)
Water heating	Upgrade to high efficiency (EF=0.63)	5%	Itron and KEMA (2008)
Natural Gas			
Water heating	Upgrade to ENERGY STAR (EF =0.67)	12%	North (2008); U.S. EPA (2008b)
Space heating	Upgrade to ENERGY STAR (AFUE=90%)	11%	RLW Analytics (2008); U.S. EPA (2008b)
Dryer	Moisture sensing dryer	10%	North (2008)

The energy efficient technology measures identified for the commercial IO sectors are summarized in Table 11. These measures in Table 11 address all key fuel end uses included in the supply chain modeling framework. Furthermore, these data represent best available measure savings estimates for the United States from two recent comprehensive studies of U.S. commercial building appliance energy efficiency potentials (Brown et al. 2008; Rosenquist et al. 2006).

Table 11: Commercial technology measure assumptions

End Use	Technology Measure	Savings
Electricity		
Computers	ENERGY STAR PCs and monitors, power management enabled	60%
Cooking	ENERGY STAR dishwashers, fryers, hot food holding cabinets	32%
Cooling	Improved HVAC systems and controls	48%
Lighting	T-8 lamps with electronic ballasts, occupancy controls, daylight dimming, improved lighting design	25%
Office Equipment	ENERGY STAR copiers and printers	25%
Other	More efficient motors in ceiling fans, pool pumps, other applications	35%
Refrigeration	High efficiency upgrades to walk-in and reach-in coolers and freezers, ice machines, etc.	38%
Space Heating	Improved HVAC systems and controls	39%
Ventilation	Improved HVAC systems and controls	45%
Natural Gas		
Space Heating	Improved shell, HVAC systems, and controls	47%
Water Heating	Higher efficiency storage and instantaneous units	10%
Other	10% reduction in miscellaneous gas use	12%
Cooking	ENERGY STAR fryer and steamer; more efficient broilers, griddles and ovens	31%

Sources: Brown et al. (2008); Rosenquist et al. (2006)

For the industrial fuel end uses in the supply chain model, the research team developed aggregate energy saving estimates for bundles of energy efficient technologies at the 3-digit IO sector level. The resulting savings estimates for thermal processes (i.e., processes based on natural gas, coal, and petroleum) for each IO sector are summarized in Table 12.

The estimates for achievable steam system fuel savings in the petroleum, chemicals, and pulp and paper industries were derived from a recent U.S. Department of Energy steam system assessment for those industries (U.S. DOE 2002). For the remaining industries, steam system savings estimates from a national-level industrial steam efficiency analysis were applied (Einstein et al. 2001). The estimates for fuel savings in process heating systems for a number of industries were derived from recent sector-specific studies by LBNL and the U.S. Department of Energy. For all other industries, and for all HVAC measures, the research team used sector-specific data from the U.S. Department of Energy's Industrial Assessment Center (IAC) database (IAC 2008). The IAC database contains energy and cost savings estimates for hundreds of different industrial technology measures, which were compiled during thousands of energy audits conducted at small and medium sized manufacturing plants in the United States since the 1980s.

Table 12: Industrial technology measure assumptions for thermal processes

	Natural gas, coal, and petroleum		
2002 IO sector(s)	**Steam systems**	**Process heat**	**HVAC**
311, 312: Food and beverage	18%	18%	25%
313, 314: Textile mills and products	18%	18%	19%
315: Apparel	18%	12%	19%
316: Leather products	18%	24%	10%
321: Lumber and wood products	18%	12%	33%
322: Paper	13%	40%	33%
323: Printing	18%	10%	14%
324: Petroleum and coal (fuel)	12%	23%	21%
325: Chemicals	12%	18%	9%
326: Plastics & rubber	18%	11%	18%
327: Nonmetallic mineral	18%	16%	20%
331: Primary metals	18%	10%	22%
332: Fabricated metals	18%	10%	22%
333: Machinery	18%	10%	10%
334: Computer & electronics	18%	10%	13%
335: Electrical equipment	18%	10%	18%
336: Transportation equip	18%	11%	17%
337: Furniture	18%	10%	14%
339: Miscellaneous	18%	10%	18%
Sources for savings estimates	IO 322, 324, and 325: U.S. DOE (2002) All others: Einstein et al. (2001)	IO 322: Jacobs & IPST (2006) IO 324: Energetics (2006) IO 325: U.S. DOE (2004) IO 327: Rue et al. (2007) Martin et al. (1999) IO 331: Choate et al. (2003) Stubbles (2000) Worrell et al. (1999) All others: IAC (2008) and KEMA (2006)	All: IAC (2008) and KEMA (2006)

Table 13 summarizes the energy savings estimates derived in this case study for energy efficient technology bundles related to industrial electricity use. The estimates for savings from motor systems are based on a comprehensive national industrial motor system inventory conducted by Xenergy (2002), which included site visits within various industrial IO sectors (including water treatment; see). The energy savings estimates for industrial HVAC, refrigeration, and lighting systems were derived using technology measure data from the IAC database.

Table 13: Industrial technology measure assumptions for electricity

	Electricity			
2002 IO sector(s)	**Motor systems**	**HVAC**	**Refrigeration**	**Lighting**
311, 312: Food and beverage	12%	14%	15%	16%
313, 314: Textile mills and products	14%	13%	10%	16%
315: Apparel	14%	14%	14%	16%
316: Leather products	12%	10%	10%	16%
321: Lumber and wood products	9%	8%	27%	16%
322: Paper	14%	25%	15%	16%
323: Printing	12%	9%	14%	16%
324: Petroleum and coal (fuel)	20%	15%	15%	16%
325: Chemicals	16%	14%	15%	16%
326: Plastics & rubber	15%	10%	21%	16%
327: Nonmetallic mineral	15%	7%	25%	16%
331: Primary metals	12%	13%	14%	16%
332: Fabricated metals	16%	11%	17%	16%
333: Machinery	15%	10%	6%	16%
334: Computer & electronics	23%	7%	11%	16%
335: Electrical equipment	13%	9%	21%	16%
336: Transportation equip	15%	9%	20%	16%
337: Furniture	13%	10%	9%	16%
339: Miscellaneous	15%	7%	5%	16%
Sources for savings estimates	All: Xenergy (2002)	All: IAC (2008) and KEMA (2006)		

Lastly, energy savings estimates associated with energy efficiency measures for motors in the agricultural and water treatment sectors are summarized in Table 14. The agricultural savings assumptions are based on recent studies of on-farm energy use and efficiency potentials in the United States by Brown and Elliott (2005a, 2005b).

Table 14: Agricultural and water treatment motor technology measure assumptions

IO sectors	Fuel	Savings	Source(s)
Agricultural	Electricity	18%	Brown and Elliott (2005a, 2005b)
Agricultural	Petroleum	23%	Brown and Elliott (2005a, 2005b)
Water treatment	Electricity	22%	Xenergy (2002)

All average savings estimates in Table 10 through Table 14 were treated as point estimates without parameter uncertainty assumptions in the modeling framework. This simplification was due primarily to lack of sufficient data to estimate credible parameter uncertainty ranges for the considered measures. However, the parameter uncertainties associated with the baseline scenario were maintained to provide some indication of the minimum uncertainty associated with the difference between the baseline and energy efficient technology scenario results for each fuel end use.

The average savings estimates in Table 10 through Table 14 are representative of best practice, currently available, and cost-effective technologies. More aggressive savings may be realized through advanced and emerging technologies; such technologies could also be evaluated in the modeling framework in future studies.

The total GHG emission reduction potential associated with the adoption of the residential and supply chain energy efficient technologies summarized in Table 10 through Table 14was estimated at around 2500 kg CO_2e per year.

Figure 6 summarizes the results by the applicable sector and fuel type. The energy efficient technologies considered for reducing home energy use accounted for roughly one-third (800 kg CO_2e) of the total estimated GHG emission reduction potential. Supply chain commercial building measures accounted for roughly 40% (1000 kg CO_2e) of the estimated GHG emission reduction potential.

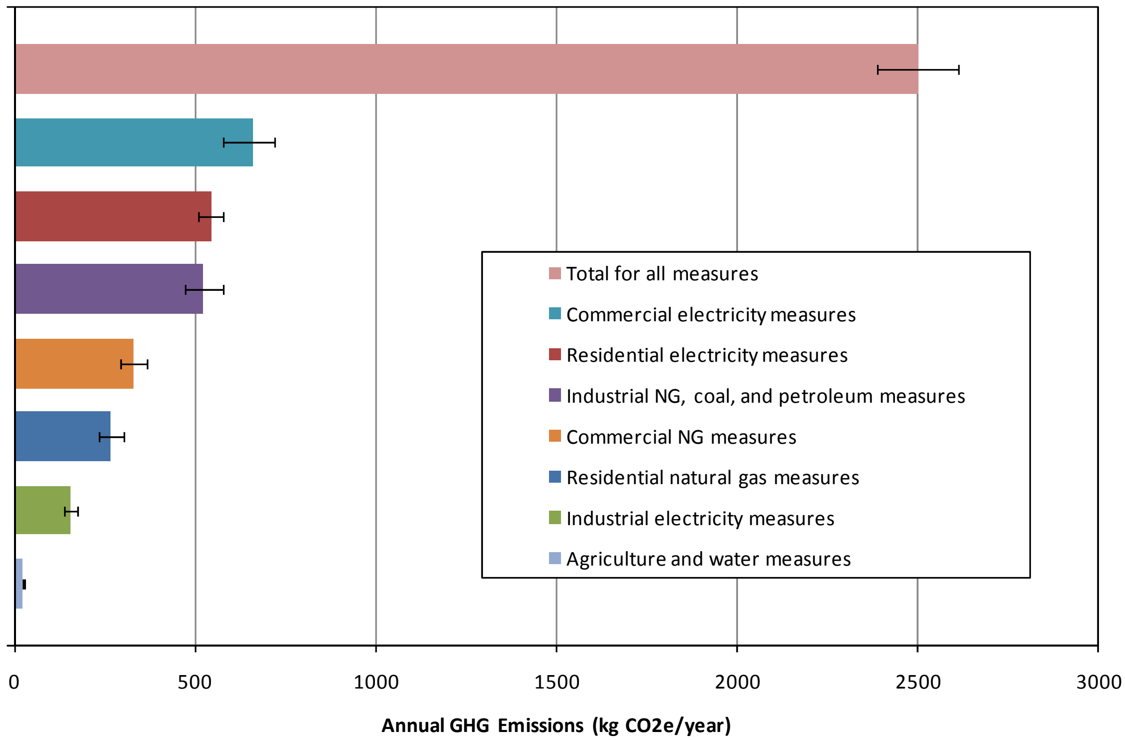

Figure 6: Estimated total GHG emissions reduction potential per household by measure type

Table 7 summarizes the estimated GHG emissions reduction potential for home energy use by fuel end use measure. These results (and those of) underscore the modeling framework's ability to provide detailed end use breakdowns, which adds useful technology improvement evaluation capabilities to California carbon footprint analyses. The results in Table 7 show that direct home energy GHG emissions from the average California household could be reduced significantly through the adoption of more energy efficient technologies. Specifically, energy efficiency upgrades to interior lighting, natural gas fired water heating and space heating technologies, personal computers, pool pumps, and refrigerators are estimated to offer the greatest GHG emission reduction potential. These seven technology measures account for roughly 90% of estimated GHG reductions in Table 7. These results suggest that in particular, these technologies should be central features of policy efforts aimed at reducing the carbon footprints of California households.

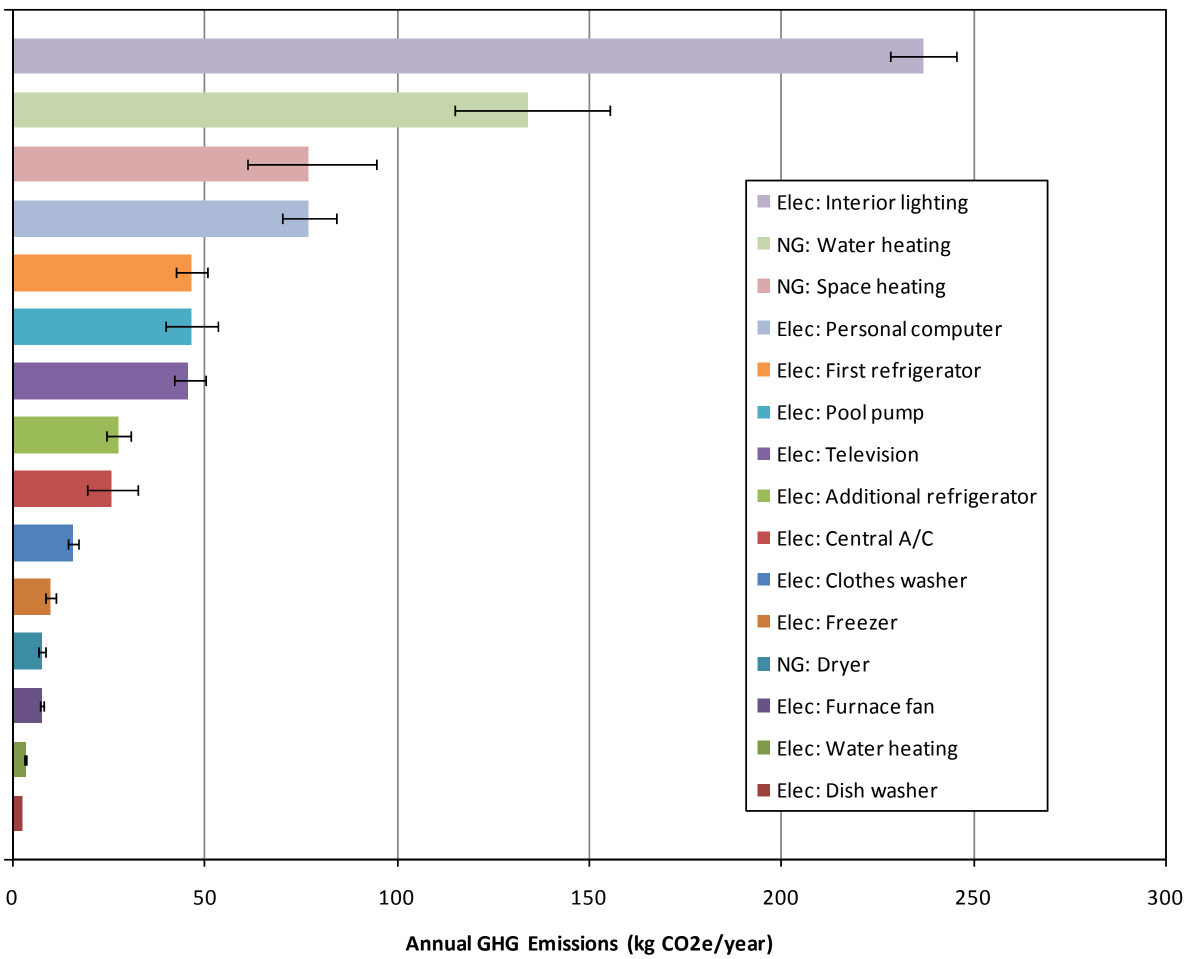

Figure 7: Estimated home energy GHG emissions reduction potential per household by measure type

A similar breakdown of supply chain GHG emissions reduction potential by end use measure type is offered in Figure 8. Results are categorized by major supply chain IO sector category (industrial, commercial, agricultural, and water treatment) and end use measure category. Over one-half of the estimated supply chain GHG emissions reduction potential is associated with the top eight measure categories, which include efficiency upgrades to commercial electrical and natural gas end uses and industrial coal end uses.

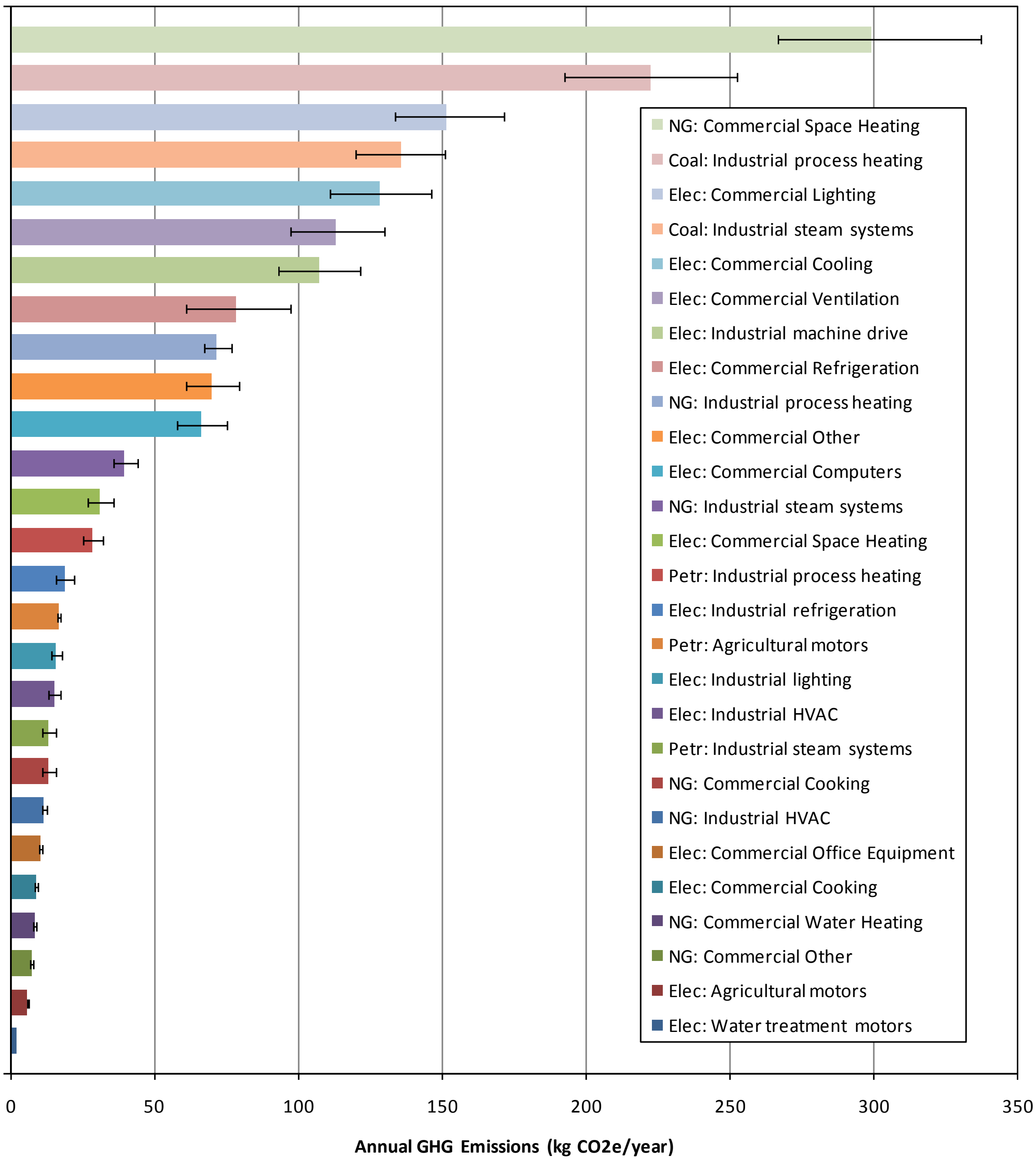

Figure 8: Estimated supply chain GHG emissions reduction potential per household by measure type

Roughly one-half (900 kg CO_2e) of the estimated supply chain potential is attributable to the commercial building measures considered in the case study; of these measures, technology upgrades to commercial HVAC and lighting systems are expected to lead to the greatest emissions reductions. The industrial measures considered in this case study account for around 40% (700 kg CO_2e) of the estimated supply chain potential. The greatest reductions in the industrial sector were expected to come from efficiency upgrades to facility process heating, steam, and motor systems.

The results in Figure 8 shed light on some of the most important opportunities for reducing the supply chain carbon footprints of California residents. Knowledge of the most significant end use efficiency opportunities can help inform policy initiatives aimed at reducing such supply chain carbon footprints. For example, green state purchasing programs could consider giving preferential treatment to supply chain partners with efficient commercial and industrial buildings, as approximated by the presence of high efficiency HVAC, lighting, process heating, steam, and motor systems in those buildings. Such information could be quickly and easily verified through facility audits or documentation of the installation of best practice equipment.

5.0 Conclusions and Recommendations

Conclusions

This project developed bottom-up and input-output approaches to estimate the household carbon footprints associated with California home energy use and the supply chains necessary for producing goods and services. This approach provides greater insight into the underlying technologies and processes contributing to the carbon footprint of California households.

The case study results suggest that over three-quarters (15,500 kg) of household GHG emissions can be attributed to the consumption of goods and services. Thus, supply chain emissions are likely to be a significant opportunity for reducing the carbon footprint of California residents.

The largest sources of electricity-based GHG emissions in the average California household were estimated to be indoor lighting, refrigeration, central air conditioning, televisions, and personal computers. The majority of GHG emissions associated with household natural gas use were attributable to two primary end uses: water heating and space heating. The two largest contributors to the supply chain carbon footprint of California residents were estimated to be food and beverages consumed at home, and the broad category of miscellaneous goods and services.

The results of the case study suggest that significant reductions in the average household carbon footprint might be realized through the adoption of energy efficient technologies in California dwellings and in the supply chains that produce goods and services purchased by Californians. For the technology measures considered, the GHG emissions reduction potential was estimated at roughly 2,500 kg CO_2e/year, or 13% of the total estimated direct and supply chain carbon footprint.

Lastly, the preliminary parameter uncertainty assessment conducted in this project revealed significant uncertainties surrounding the average carbon footprint estimates generated by the model. Large uncertainties in the non-energy supply chain GHG emission factors are particularly important to acknowledge when interpreting the results of this project.

Recommendations

The research team identified a number of opportunities for future research that could improve and expand upon the bottom-up, IO-based modeling framework developed in this project:

- Improved fuel end use models could be developed for supply chain petroleum uses—particularly in the transportation sector—and uses of biomass, waste, and other fuels. The research team was only able to offer a preliminary disaggregation of petroleum use based on available data, which centered on a few key end uses. No end use breakdowns were developed for biomass, waste, and other fuels due to lack of readily-available data on the composition of and end uses for these fuels. However, end use breakdowns for petroleum and biomass, waste, and other fuels could be developed based on more detailed study of individual IO sectors.

- A more comprehensive parameter uncertainty could be conducted on fuel use, fuel end use, and measure savings data in the model. The research team only included readily-available parameter uncertainty information from the major survey data used in this project; however, parameter uncertainty estimates for other key variables could be developed based on a thorough search of available data sources.
- A preliminary modeling uncertainty assessment could be performed by constructing different plausible model structures for mapping fuel and GHG emissions data to IO sectors, and further mapping those data to specific fuel end uses. These results of different model structure options could be compared to arrive at preliminary estimates of modeling uncertainty.
- More measures could be included in future assessments of technologies for reducing the direct and supply chain GHG emissions of California residents (most notably, supply chain transportation measures). In the case study conducted in this project, the research team focused on identifying only a core set of well-known measures for which credible energy savings estimates could be derived. However, many other technology measures could be evaluated using the modeling framework. Additionally, the economics of those measures could be included in future analyses to arrive at estimates for the cost of achieving various levels of direct and supply chain GHG emissions reductions.
- The bottom-up supply chain modeling framework could be applied to MRIO models that disaggregate supply chain transactions using trade statistics. Such an approach could better reflect differences in fuel end uses, efficiencies, and available GHG emissions reductions potentials across global supply chains. Moreover, such an approach would better approximate the geographical characteristics of supply chains for goods and services purchased by Californians, including in-state supply chains where energy efficiencies and fuel sources may differ significantly from national averages.
- The modeling framework could be applied to estimate the GHG emission potentials associated with other important carbon footprint reduction opportunities, including behavioral changes, changes to purchased products, technologies for reducing non-energy GHG emissions, and changes to home and supply chain energy sources.

Benefits to California

The results of this project provide two important contributions toward improved California-specific household carbon footprint analysis. First, the direct and supply chain GHG emissions modeling frameworks developed in this project provide greater bottom-up end use detail than existing carbon calculators. This bottom-up detail allows California energy and policy analysts to better understand the underlying technologies and processes contributing to the carbon footprint of California households, and to better assess specific technology improvement options for reducing the personal carbon footprints of California residents.

Second, the preliminary parameter uncertainty assessments conducted in this project provide much needed information on the minimum uncertainty surrounding carbon footprint estimates, which will help California energy and policy analysts better assess the usefulness (and limitations) of carbon footprint estimates toward policy decisions. The contributions of this project should therefore improve the state of the art in carbon footprint analyses for California, which can help researchers and policy analysts identify strategies for reducing the carbon footprints of California residents with greater confidence.

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Glossary

CARB	California Air Resources Board
CBECS	Commercial Building Energy Consumption Survey
CH_4	Methane
CMU	Carnegie Mellon University
CO_2	Carbon dioxide
CO_2e	Carbon dioxide equivalent
EIO-LCA	Economic Input-Output Life-Cycle Assessment
GHG	Greenhouse gas
GWP	Global warming potential
HVAC	Heating, ventilation, and air conditioning
IO	Input-output
IPCC	Intergovernmental Panel on Climate Change
kg	Kilogram
kWh	Kilowatt-hour
LCA	Life-cycle assessment
MECS	Manufacturing Energy Consumption Survey
MJ	Megajoule
MRIO	Multi-regional input-output
N_2O	Nitrous oxide
NAICS	North American Industry Classification System
RASS	Residential Appliance Saturation Survey
RECS	Residential Energy Consumption Survey

Appendix

Detailed assumptions for average U.S. household 2002 consumer expenditures

2002 IO Sector	IO Sector Description	2002 Expenditure ($ Producer Price)	Standard Deviation	Consumption Category
111200	Vegetable and melon farming	81.58	1.42	Food and non-alcoholic beverages at home
111400	Greenhouse, nursery, and floriculture production	25.88	0.85	Miscellaneous goods and services
112300	Poultry and egg production	23.12	0.57	Food and non-alcoholic beverages at home
221300	Water, sewage and other systems	237.16	4.19	Household services
230302	Residential maintenance and repair	490.06	15.00	Household furnishings, equipment, and maintenance
311111	Dog and cat food manufacturing	81.97	1.90	Miscellaneous goods and services
311210	Flour milling and malt manufacturing	24.17	0.50	Food and non-alcoholic beverages at home
311225	Fats and oils refining and blending	25.16	0.58	Food and non-alcoholic beverages at home
311230	Breakfast cereal manufacturing	56.02	1.16	Food and non-alcoholic beverages at home
311310	Sugar cane mills and refining	2.34	0.06	Food and non-alcoholic beverages at home
311320	Chocolate and confectionery manufacturing from cacao beans	14.12	0.34	Food and non-alcoholic beverages at home
311340	Nonchocolate confectionery manufacturing	48.27	1.17	Food and non-alcoholic beverages at home
311410	Frozen food manufacturing	115.93	3.01	Food and non-alcoholic beverages at home
311420	Fruit and vegetable canning, pickling, and drying	160.56	3.14	Food and non-alcoholic beverages at home
311513	Cheese manufacturing	62.22	0.96	Food and non-alcoholic beverages at home
311520	Ice cream and frozen dessert manufacturing	42.27	0.66	Food and non-alcoholic beverages at home
311615	Poultry processing	99.29	2.48	Food and non-alcoholic beverages at home
311700	Seafood product preparation and packaging	74.02	3.01	Food and non-alcoholic beverages at home
311810	Bread and bakery product manufacturing	138.40	1.98	Food and non-alcoholic beverages at home

2002 IO Sector	IO Sector Description	2002 Expenditure ($ Producer Price)	Standard Deviation	Consumption Category
311820	Cookie, cracker, and pasta manufacturing	60.63	0.98	Food and non-alcoholic beverages at home
311910	Snack food manufacturing	71.16	1.27	Food and non-alcoholic beverages at home
311920	Coffee and tea manufacturing	30.50	0.51	Food and non-alcoholic beverages at home
311940	Seasoning and dressing manufacturing	77.82	1.43	Food and non-alcoholic beverages at home
311990	All other food manufacturing	54.06	0.94	Food and non-alcoholic beverages at home
312110	Soft drink and ice manufacturing	101.25	1.67	Food and non-alcoholic beverages at home
312120	Breweries	83.27	3.30	Food and non-alcoholic beverages at home
312130	Wineries	55.68	2.17	Alcoholic beverages and tobacco
312140	Distilleries	57.37	2.26	Alcoholic beverages and tobacco
313100	Fiber, yarn, and thread mills	4.92	0.23	Clothing and footwear
313210	Broadwoven fabric mills	2.15	0.08	Clothing and footwear
314110	Carpet and rug mills	19.22	1.88	Household furnishings, equipment, and maintenance
314120	Curtain and linen mills	59.67	2.77	Household furnishings, equipment, and maintenance
314910	Textile bag and canvas mills	16.02	0.53	Recreation and culture
314990	All other textile product mills	3.38	0.16	Household furnishings, equipment, and maintenance
315100	Apparel knitting mills	15.49	0.69	Clothing and footwear
315210	Cut and sew apparel contractors	27.25	1.00	Clothing and footwear
315220	Men's and boys' cut and sew apparel manufacturing	186.28	8.46	Clothing and footwear
315230	Women's and girls' cut and sew apparel manufacturing	263.39	11.22	Clothing and footwear
315900	Apparel accessories and other apparel manufacturing	17.05	0.72	Clothing and footwear
316200	Footwear manufacturing	128.59	5.31	Clothing and footwear
316900	Other leather and allied product manufacturing	2.50	0.08	Miscellaneous goods and services
321910	Wood windows and doors and millwork	13.86	0.40	Household furnishings, equipment, and maintenance
322291	Sanitary paper product manufacturing	45.97	7.03	Miscellaneous goods and services

2002 IO Sector	IO Sector Description	2002 Expenditure ($ Producer Price)	Standard Deviation	Consumption Category
322299	All other converted paper product manufacturing	18.82	0.65	Miscellaneous goods and services
323110	Printing	4.11	0.15	Clothing and footwear
324122	Asphalt shingle and coating materials manufacturing	1.92	0.06	Household furnishings, equipment, and maintenance
325320	Pesticide and other agricultural chemical manufacturing	61.36	9.37	Miscellaneous goods and services
325411	Medicinal and botanical manufacturing	0.05	0.00	Health Care
325412	Pharmaceutical preparation manufacturing	279.54	6.44	Health care
325510	Paint and coating manufacturing	7.76	0.23	Household furnishings, equipment, and maintenance
325610	Soap and cleaning compound manufacturing	69.87	1.90	Miscellaneous goods and services
325620	Toilet preparation manufacturing	211.76	12.31	Miscellaneous goods and services
327212	Other pressed and blown glass and glassware manufacturing	3.00	0.20	Household furnishings, equipment, and maintenance
327330	Concrete pipe, brick, and block manufacturing	0.63	0.02	Household furnishings, equipment, and maintenance
327992	Ground or treated mineral and earth manufacturing	6.84	0.21	Household furnishings, equipment, and maintenance
327993	Mineral wool manufacturing	14.24	0.42	Household furnishings, equipment, and maintenance
332310	Plate work and fabricated structural product manufacturing	15.57	1.02	Household furnishings, equipment, and maintenance
332500	Hardware manufacturing	7.05	0.23	Miscellaneous goods and services
333112	Lawn and garden equipment manufacturing	20.83	0.69	Miscellaneous goods and services
333315	Photographic and photocopying equipment manufacturing	11.38	0.96	Miscellaneous goods and services
333415	Air conditioning, refrigeration, and warm air heating equipment manufacturing	19.32	0.69	Household furnishings, equipment, and maintenance

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333991	Power-driven handtool manufacturing	15.86	0.53	Miscellaneous goods and services
334111	Electronic computer manufacturing	87.07	2.89	Miscellaneous goods and services
334210	Telephone apparatus manufacturing	0.40	0.01	Communications
334220	Broadcast and wireless communications equipment	21.46	0.71	Miscellaneous goods and services
334290	Other communications equipment manufacturing	0.92	0.03	Household furnishings, equipment, and maintenance
334300	Audio and video equipment manufacturing	86.84	1.45	Miscellaneous goods and services
334412	Bare printed circuit board manufacturing	12.93	0.22	Miscellaneous goods and services
334510	Electromedical and electrotherapeutic apparatus manufacturing	6.55	0.23	Health care
334613	Magnetic and optical recording media manufacturing	48.91	0.81	Miscellaneous goods and services
335210	Small electrical appliance manufacturing	46.64	2.04	Miscellaneous goods and services
335221	Household cooking appliance manufacturing	31.14	1.13	Household furnishings, equipment, and maintenance
335222	Household refrigerator and home freezer manufacturing	31.72	1.15	Household furnishings, equipment, and maintenance
335224	Household laundry equipment manufacturing	34.75	1.24	Household furnishings, equipment, and maintenance
335228	Other major household appliance manufacturing	8.30	0.30	Household furnishings, equipment, and maintenance
335999	All other miscellaneous electrical equipment and component manufacturing	8.06	0.17	Household furnishings, equipment, and maintenance
336214	Travel trailer and camper manufacturing	22.43	1.88	Miscellaneous goods and services
336612	Boat building	12.02	1.04	Miscellaneous goods and services
336991	Motorcycle, bicycle, and parts manufacturing	7.51	0.63	Recreation and culture
337121	Upholstered household furniture manufacturing	61.10	2.74	Household furnishings, equipment, and maintenance

2002 IO Sector	IO Sector Description	2002 Expenditure ($ Producer Price)	Standard Deviation	Consumption Category
337122	Nonupholstered wood household furniture manufacturing	66.19	2.98	Household furnishings, equipment, and maintenance
337212	Office furniture and custom architectural woodwork and millwork manufacturing	5.48	0.18	Miscellaneous goods and services
337910	Mattress manufacturing	27.12	1.20	Household furnishings, equipment, and maintenance
337920	Blind and shade manufacturing	6.46	0.22	Household furnishings, equipment, and maintenance
339112	Surgical and medical instrument manufacturing	2.01	0.07	Health care
339115	Ophthalmic goods manufacturing	20.96	0.77	Health care
339910	Jewelry and silverware manufacturing	46.53	1.81	Household furnishings, equipment, and maintenance
339920	Sporting and athletic goods manufacturing	54.87	4.61	Recreation and culture
339930	Doll, toy, and game manufacturing	50.72	1.18	Recreation and culture
339940	Office supplies (except paper) manufacturing	21.99	1.53	Education
339992	Musical instrument manufacturing	10.12	0.17	Miscellaneous goods and services
339994	Broom, brush, and mop manufacturing	1.12	0.04	Household furnishings, equipment, and maintenance
484000	Truck transportation	33.13	0.89	Miscellaneous goods and services
491000	Postal service	71.24	2.50	Miscellaneous goods and services
493000	Warehousing and storage	0.55	0.02	Clothing and footwear
511110	Newspaper publishers	46.27	0.90	Recreation and culture
511120	Periodical publishers	21.29	0.41	Recreation and culture
511130	Book publishers	67.38	3.03	Recreation and culture
511200	Software publishers	12.85	0.43	Miscellaneous goods and services
515200	Cable and other subscription programming	382.28	6.46	Miscellaneous goods and services
517000	Telecommunications	956.75	10.14	Communications
519100	Other information services	107.29	2.96	Miscellaneous goods and services
524100	Insurance carriers	1334.91	21.25	Health care

2002 IO Sector	IO Sector Description	2002 Expenditure ($ Producer Price)	Standard Deviation	Consumption Category
524200	Insurance agencies, brokerages, and related activities	708.01	23.07	Miscellaneous goods and services
532230	Video tape and disc rental	39.33	0.68	Miscellaneous goods and services
532400	Commercial and industrial machinery and equipment rental and leasing	1.36	0.09	Miscellaneous goods and services
541100	Legal services	172.76	6.53	Miscellaneous goods and services
541200	Accounting, tax preparation, bookkeeping, and payroll services	57.85	2.16	Miscellaneous goods and services
541920	Photographic services	20.42	1.74	Recreation and culture
541940	Veterinary services	71.44	1.70	Miscellaneous goods and services
561600	Investigation and security services	24.21	0.71	Household furnishings, equipment, and maintenance
561700	Services to buildings and dwellings	276.24	8.36	Household furnishings, equipment, and maintenance
561900	Other support services	3.15	0.09	Miscellaneous goods and services
562000	Waste management and remediation services	91.14	1.64	Household services
611100	Elementary and secondary schools	128.94	8.93	Education
622000	Hospitals	88.08	2.98	Health care
623000	Nursing and residential care facilities	19.27	0.98	Miscellaneous goods and services
624400	Child day care services	274.13	22.06	Miscellaneous goods and services
711100	Performing arts companies	143.87	4.00	Recreation and culture
711200	Spectator sports	51.37	1.44	Recreation and culture
712000	Museums, historical sites, zoos, and parks	25.64	0.72	Recreation and culture
713940	Fitness and recreational sports centers	295.16	8.15	Recreation and culture
722000	Food services and drinking places	2276.32	38.58	Restaurants and hotels
811200	Electronic and precision equipment repair and maintenance	6.64	0.16	Household furnishings, equipment, and maintenance
811400	Personal and household goods repair and maintenance	94.14	2.93	Household furnishings, equipment, and maintenance
812100	Personal care services	298.88	9.42	Miscellaneous goods and services

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812200	Death care services	93.96	3.55	Miscellaneous goods and services
812300	Dry-cleaning and laundry services	113.12	4.17	Miscellaneous goods and services
812900	Other personal services	48.55	2.74	Miscellaneous goods and services
1113A0	Fruit farming	90.08	1.90	Food and non-alcoholic beverages at home
31131A	Sugar cane mills and refining	9.96	0.24	Food and non-alcoholic beverages at home
31151A	Fluid milk and butter manufacturing	124.82	1.93	Food and non-alcoholic beverages at home
31161A	Animal (except poultry) slaughtering, rendering, and processing	337.10	8.19	Food and non-alcoholic beverages at home
3122A0	Tobacco product manufacturing	198.36	7.00	Alcoholic beverages and tobacco
3259A0	All other chemical product and preparation manufacturing	8.79	0.75	Miscellaneous goods and services
32619A	Other plastics product manufacturing	16.48	0.85	Household furnishings, equipment, and maintenance
32711A	Pottery, ceramics, and plumbing fixture manufacturing	6.68	0.45	Household furnishings, equipment, and maintenance
32712A	Brick, tile, and other structural clay product manufacturing	4.74	0.14	Household furnishings, equipment, and maintenance
33221A	Cutlery, utensil, pot, and pan manufacturing	1.57	0.10	Household furnishings, equipment, and maintenance
33221B	Handtool manufacturing	4.02	0.13	Miscellaneous goods and services
33329A	Other industrial machinery manufacturing	2.65	0.10	Household furnishings, equipment, and maintenance
33331A	Vending, commercial, industrial, and office machinery manufacturing	9.97	0.37	Miscellaneous goods and services
33451A	Watch, clock, and other measuring and controlling device manufacturing	8.58	0.31	Clothing and footwear
33712A	Metal and other household furniture (except wood) manufacturing	33.52	1.53	Household furnishings, equipment, and maintenance
33721A	Wood television, radio, and sewing machine cabinet manufacturing	13.61	0.57	Recreation and culture
33999A	All other miscellaneous manufacturing	77.76	2.52	Miscellaneous goods and services

2002 IO Sector	IO Sector Description	2002 Expenditure ($ Producer Price)	Standard Deviation	Consumption Category
48A000	Scenic and sightseeing transportation and support activities for transportation	6.66	0.57	Recreation and culture
52A000	Monetary authorities and depository credit intermediation	4163.38	87.33	Miscellaneous goods and services
532A00	General and consumer goods rental except video tapes and discs	10.52	0.34	Miscellaneous goods and services
611A00	Junior colleges, colleges, universities, and professional schools	1001.74	62.16	Education
611B00	Other educational services	51.30	3.52	Education
621A00	Offices of physicians, dentists, and other health practitioners	479.82	16.38	Health care
621B00	Medical and diagnostic labs and outpatient and other ambulatory care services	9.46	0.32	Health care
713A00	Amusement parks, arcades, and gambling industries	57.99	2.62	Recreation and culture
7211A0	Hotels and motels, including casino hotels	252.87	13.23	Restaurants and hotels
813A00	Grantmaking, giving, and social advocacy organizations	675.48	36.87	Miscellaneous goods and services
813B00	Civic, social, professional, and similar organizations	44.32	2.40	Miscellaneous goods and services
S00203	Other state and local government enterprises	1306.12	32.27	Miscellaneous goods and services
S00500	General Federal defense government services	2676.01	43.66	Miscellaneous goods and services