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Consumption Based Greenhouse Gas Inventory of San Francisco from 1990 to 2015

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Consumption-Based Greenhouse Gas Inventory of San Francisco from 1990 to 2015

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Abstract

This study developed a consumption-based emissions inventory (CBEI) for the City and County of San Francisco, California from 1990 to 2015. CBEIs allocate all greenhouse gas emissions throughout product and service supply chains to final demand, namely households and governments.

We find that average household carbon footprints in San Francisco decreased by 17% over the 25-year study period, and were 21% lower than the national average by 2015. Low rates of motor vehicle usage, small home (building) size, small household size, high prevalence of renters, population density, moderate climate, and relatively low-carbon electricity all contributed to lower consumption-based emissions. These factors outweighed the countervailing effects of income and education, which tend to increase consumption and associated carbon footprints. Despite progress at reducing emissions on a per household basis, on aggregate, the total city-wide CBEI was only 2% lower in 2015 compared to 1990 levels. This reality reflects population pressures and the challenge of reducing emissions that depend on global supply chains.

Traditional GHG inventories tend to neglect the effect of consumer demand on supply chain emissions, thus underestimating a city's total impact. San Francisco's CBEI is 2.5 times larger than the city's traditional, more limited inventory. Tracking of full consumption-based inventories over time should aid in the development of new targets, policies, programs, incentives, and communications based on the unique opportunities for responsible production and consumption within San Francisco.

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Executive Summary

Overview

This study developed a consumption-based greenhouse gas (GHG) inventory for the City and County of San Francisco, California for the years 1990 through 2015. This type of inventory, known as a CBEI, sums up the carbon footprints of all energy, transportation, food, goods, and services consumed by households and governments, regardless of where the emissions occur. CBEIs consider full life cycle emissions, including resource extraction, production, transport, trade, use, and disposal; for most products, the majority of emissions are generated during production.

The calculations in the CBEI are based on estimates of consumer spending and corresponding GHG emission factors. This view of emissions is intended to be an alternative to the traditional (sector- or territorial-based) inventories typically performed by cities, which count emissions from the city's physical boundaries and not beyond. Conducting an inventory through the lens of a CBEI presents opportunities to address global GHG emissions from the life cycle of goods and services consumed within communities, regardless of whether omissions physically occur within the city's geographic boundaries.

Background

The use of consumption-based inventories is quite recent (less than 15 years old) and methods for calculating CBEIs are still evolving. San Francisco was an early pioneer in the field, conducting two previous CBEIs for the years 2000 and 2008 (Stanton et al. 2011). According to the 2008 estimate, total consumption-based emissions were roughly three times larger than the traditional GHG inventory (21.7 vs. 8.5 million metric tons CO₂e) and San Francisco's emissions were 24% higher than California's on a per capita basis (28.3 vs. 22.8 tons CO₂e per person, respectively) (SEI, 2008). However, the 2008 methodology was flawed because income alone was used to estimate variation in consumption across different geographic areas. Another CBEI was conducted for all cities in the San Francisco Bay Area (Jones 2015) similarly relied on income and household size to estimate consumption of food, goods, and services. The 2020 study greatly improves upon these previous methodologies.

Methods

A number of methodological advances were made in the current study to improve CBEIs. We use econometric analysis of national household survey data to uncover the main drivers of consumption for each product category (e.g., meat, furniture, vehicle usage), and then estimate consumption in San Francisco based on variation in these drivers compared to national averages. These main drivers include

- demographics (income, household size, race, education),
- home characteristics (home size, home ownership, structure type, heating fuel),
- travel behavior (vehicle ownership, commute mode, commute times),
- geographic variables (population density, weather), and

- economic data (energy prices).

Based on this information, we estimated carbon footprints for every census tract in San Francisco, and for the city overall, from 1990 through 2015. We included local data instead of modeled data wherever possible.

Major Findings

San Francisco's CBEI shows that 14.72 million metric tons of CO₂e were emitted in 2015, which is 2.5 times higher than GHG emissions under the traditional (sector-based) inventory approach of 5.93 million metric tons (Figure A). Total city-wide consumption-based emissions (CBEs) did not change much over the study period: there was a 2% decrease between 1990 and 2015. From a total CBE lens, any progress made in emission reductions since 1990 was balanced by an increasing population. The CBEI shows emissions were 1.9 to 2.5 times the traditional inventory from 1990 to 2015, highlighting the need for San Francisco's climate action to now include responsible production and consumption policy and establish programs to further mitigate emissions.

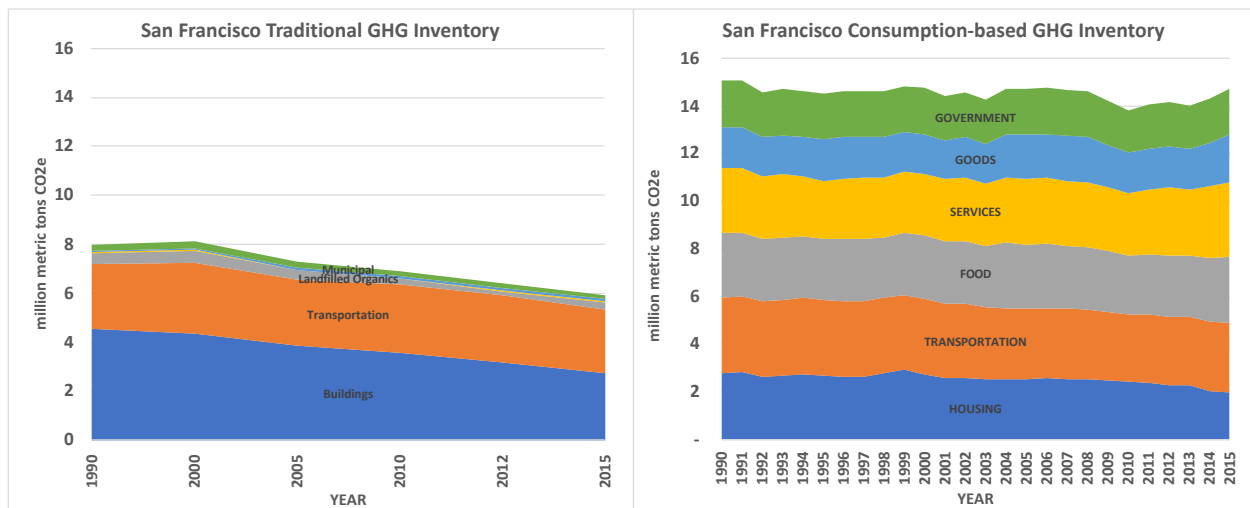


Figure A. San Francisco's Traditional GHG Inventory (left-hand figure) vs. Consumption-based GHG Inventory (right-hand figure) for the year 2015.

In contrast to measuring total (absolute) emissions over time, a preferred way to track emissions progress is to measure CBEs on a per household basis. A **household carbon footprint** refers to the GHG emissions resulting from the full life cycle of all household expenditures. Since 1990, emissions on a per household basis have declined by 17% (from 42.9 to 35.6 metric tons per household), with the largest reductions from energy (-38%), transportation (-22%), and food (-14%) (Figure B). Reductions in energy were due to the decarbonization of grid electricity and lower residential natural gas consumption. Improvements in vehicle fuel economy resulted in lower transportation emissions. Emissions from food followed national trends of less red meat consumption and assumed slow decarbonization of supply chains. Importantly, the carbon footprint of goods and services consumed by San Francisco households remained relatively unchanged over the study period. This underscores the challenge of

addressing full consumption-based emissions, particularly when they are not consistently monitored over time.

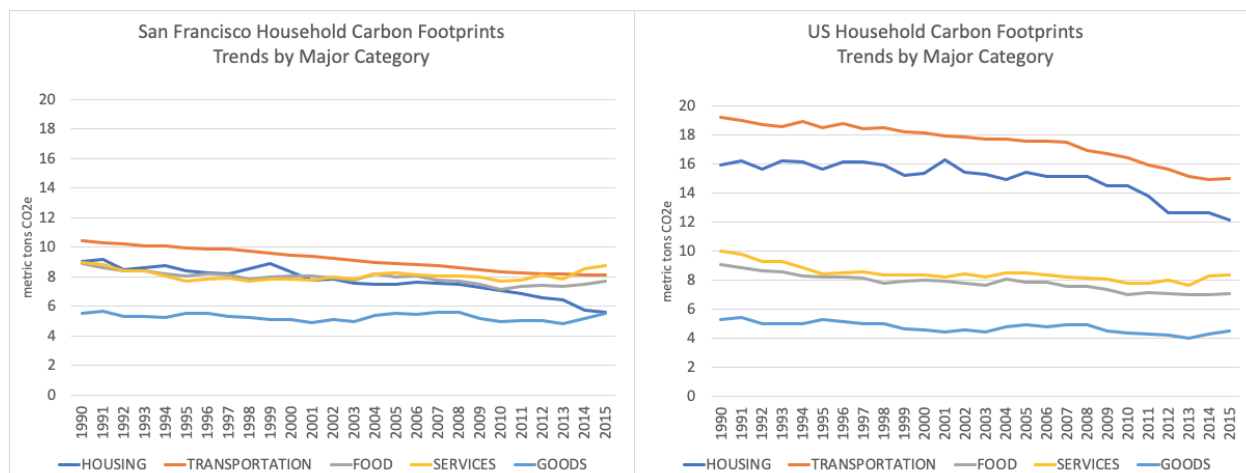


Figure B. San Francisco and U.S. Household Carbon Footprint Trends by Major Category: 1990 to 2015

In 2015, average household carbon footprints in San Francisco were 21% lower than the national average (35.6 vs. 45.3 tons of CO₂e per household, respectively) (Figure B). San Francisco households produced only 3.6 metric tons of CO₂e from motor vehicle fuel compared to 10 metric tons of CO₂e for the average U.S. household. Electricity was a large source of household carbon footprints in the U.S., but only a small contributor to household carbon footprints in San Francisco. Emissions from goods and services were only slightly higher than the national average. Higher income and education levels tend to increase consumption, but these effects were outweighed by low rates of vehicle ownership, small home (building) size, small household size, low rates of home ownership, high population density, moderate climate, and relatively low-carbon electricity, among other factors.

Transportation was the largest contributor to San Francisco household carbon footprints in 1990. In 2015, the services category (24%) was the largest contributor to household carbon footprints, followed by transportation (23%), food (21%), goods (16%), and housing (16%) (Figure C). These five major categories were further broken into 24 subcategories, several of which may be further disaggregated, such as “other food,” “other goods,” and “other services.” The largest subcategories include healthcare (3.7 tons per household), motor vehicle fuel (3.6 tons), air travel (3.2 tons), “eating out,” including take-out and delivery (2.3 tons), natural gas (2.2 tons), and “shelter”, also known as “home construction” (1.6 tons).

Carbon footprints varied dramatically between neighborhoods (census tracts) within San Francisco, due to differences in key driving factors such as household size, home size, income, ownership rates, education level, vehicle ownership, population density, home heating fuels, and home structure (Figure D). There is a four-fold difference between household carbon footprints in the lowest carbon footprint neighborhoods, located near San Francisco’s financial district, and the highest carbon footprint locations, mostly in the southern half of the city.

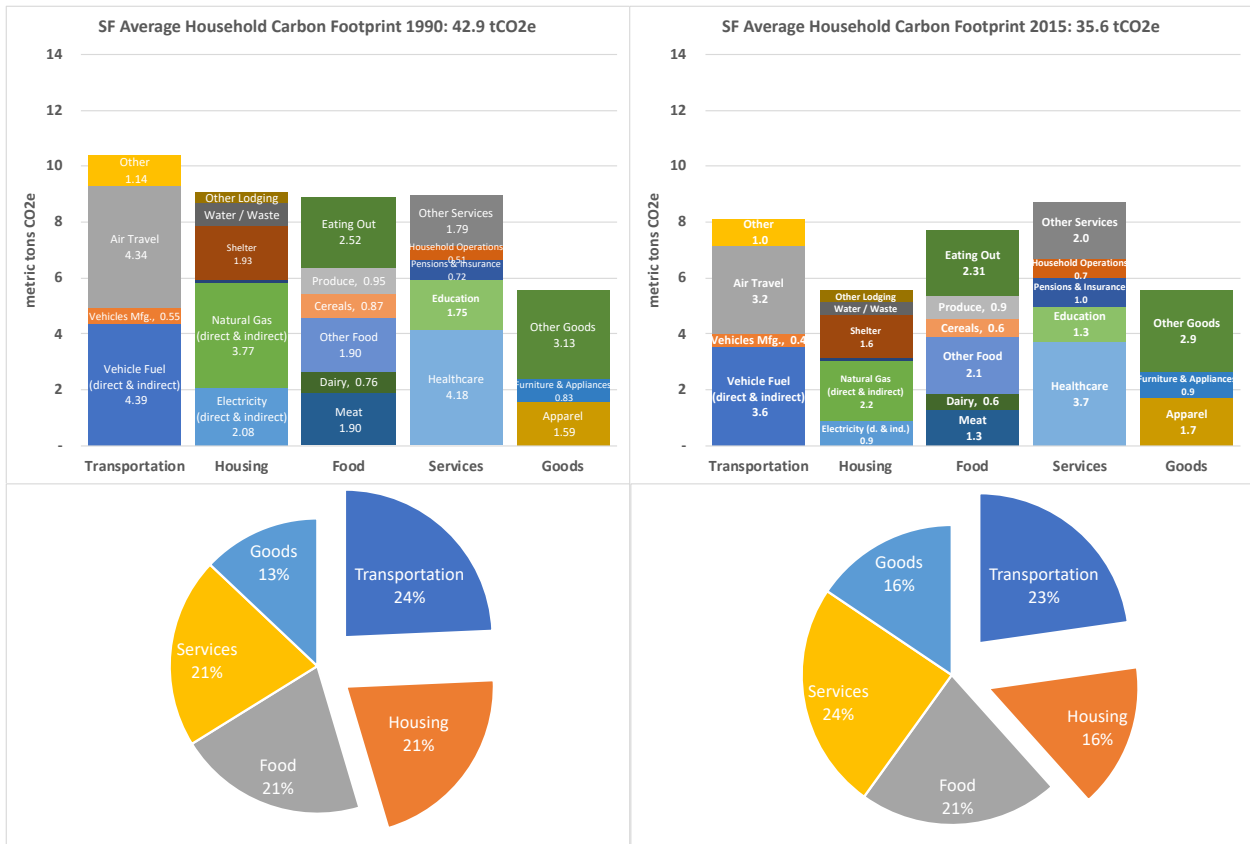


Figure C. Average San Francisco Household Carbon Footprints in 1990 and 2015

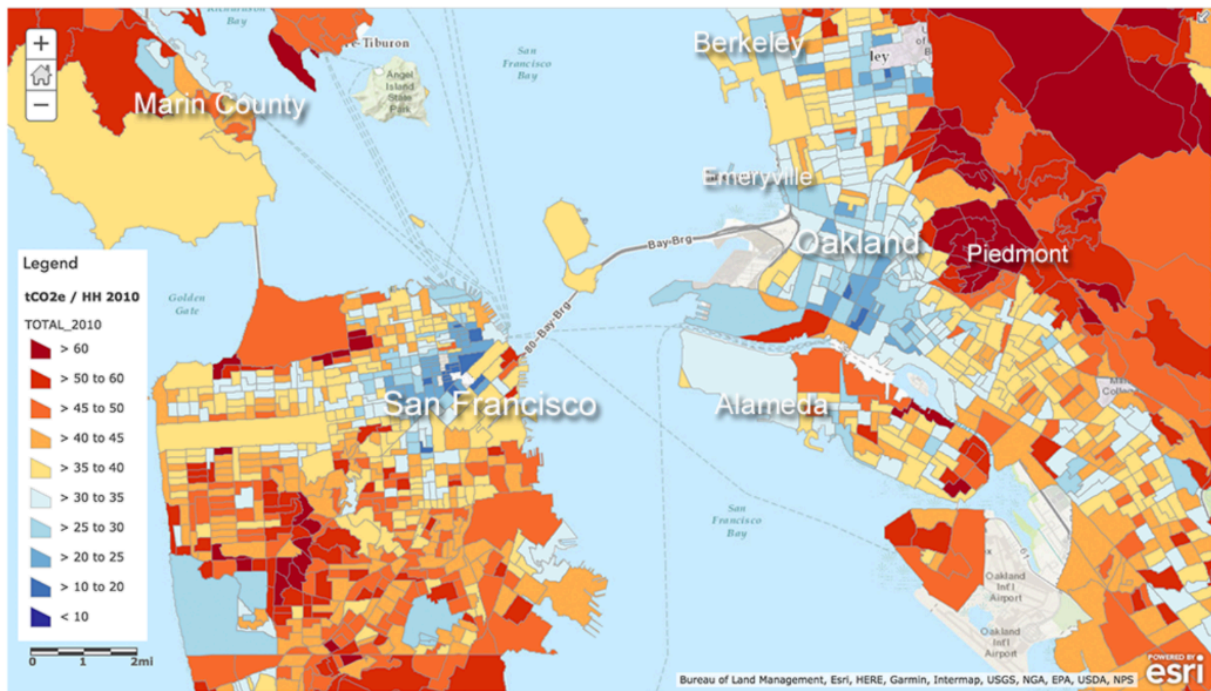


Figure D. Average household carbon footprints in San Francisco Bay Area. <https://coolclimate.org/scenarios>

Policy Relevance

The impact of local activities on generating GHG emissions may be viewed from multiple perspectives, with different implications for local policy. This study presents results from a production to consumption perspective, in which all global GHG emissions are allocated to final demand, i.e., households and government activities. Tracking consumption-based inventories over time will help to inform the development of targets, policies, programs, incentives, and communications by uncovering unique opportunities to increase responsible production and consumption within San Francisco.

Developing policy from CBEIs is a new and emerging field. A major benefit of the approach is the ability to compare carbon footprints and reduction opportunities at different spatial resolutions, from neighborhood to national scales. For example, policies applied to low-income, high density communities should be categorically different from policies applied to high income suburbs, since both the size and composition of carbon footprints will be very different. Similarly, the contribution of food, goods, and services as a percentage of total carbon footprints was higher in San Francisco than for the nation as a whole (61% vs 44%, respectively) in 2015. The city has already done a lot to reduce emissions from energy and transportation. Additional effort is now needed to address full consumption-based emissions.

Existing climate action policies and programs built upon the traditional inventory, such as building electrification and energy efficiency, expanding community choice aggregation customer base, transit first policy, and zero waste, have had and continue to have a significant impact. By also conducting and tracking consumption-based emissions, San Francisco may bolster existing policies, programs, and incentives and surface new ones, deepening and expanding its GHG reduction efforts. Some of these efforts might include:

- encouraging urban infill where carbon footprints are lowest
- eliminating natural gas
- dematerialization (i.e., shifting expenditures from goods to services to information)
- reducing meat and dairy consumption in businesses and institutions such as government, schools, and hospitals
- reducing consumption of and purchasing fewer carbon-intense consumer goods and services
- encouraging local consumption, particularly of services and information
- promoting and improving green procurement standards for businesses and institutions
- reducing residents' air travel emissions
- lowering embodied carbon of construction materials
- conducting behavioral campaigns to activate, educate, motivate, and empower individuals and organizations to reduce their carbon footprints
- Tailoring interventions at neighborhood scales, e.g., promoting higher cost options, such as electric appliances and vehicles, in higher income neighborhoods, and promoting income-qualified energy assistance programs in lower income neighborhoods.

These policy recommendations are only preliminary and deserve considerably more analysis, discussion and vetting before being applied at scale. As a start, setting a consumption-based emissions reduction target to accompany San Francisco's sector-based target would aid in the development of policies, programs, and incentives to address CBEs. Furthermore, an emissions target indicator based on a per household or per capita rather than an absolute (total) basis should be established as a highly preferable metric because it would be more policy relevant, better reflecting the impact of policies and programs set by San Francisco as well as the State. Such a target should reflect current trends, statewide targets, local resources, and new and promising technologies and behavioral interventions to engage households, businesses, institutions, and city government in meaningful collective climate action.

Introduction

Demand for goods and services drives global emission of greenhouse gases. Consumption-based emissions inventories (CBEIs) have emerged in recent years as a complement to traditional, territorial-based inventories. The consumption-based approach allocates all global greenhouse gas (GHG) emissions to final demand, mostly households and government, regardless of where they occur in global supply chains. Both approaches could be fully comprehensive; if all countries or subnational geographies conducted either method, the total would equal global emissions. While national governments use territorial-based methods to develop inventories and set emission reduction targets, local governments are increasingly turning to consumption-based approaches to track the full life cycle impact on global emissions of goods and services consumed locally. In contrast to the territorial approach, which focuses on emissions where they physically enter the atmosphere, CBEIs consider complete systems of production and consumption using a life cycle assessment (LCA) methodology.

Two previous consumption-based emissions inventories have been conducted for San Francisco. According to the most recent 2008 estimate (SEI 2011), total consumption-based emissions were roughly three times larger than the traditional GHG inventory (21.7 vs. 8.5 million metric tons (t) CO₂e) and San Francisco's emissions were 24% higher than California on a per capita basis (28.3 vs. 22.8 tCO₂e per person). Perhaps most surprising, emissions from food, goods and services in the 2008 CBEI were estimated to be 41% higher than the California average; food alone was estimated at 70% higher than average. Higher than average incomes in San Francisco entirely account for the differences in the study. The 2008 CBEI uses the proprietary IMPLAN model to estimate household consumption and IMPLAN relies exclusively on income to differentiate consumption between local and national scales. A major problem of the income-only approach is households of different income levels in the United States are also different in other fundamental ways. High income households tend to live in low density, suburban neighborhoods with more people per household, living in larger, owned homes compared to San Francisco households. The IMPLAN model assumes consumption to be the same at similar income levels, regardless of these other factors, which may also influence consumption. Addressing the effect of significant demographic, geographic and physical drivers of consumption is critical for accurate consumption-based inventories.

A number of methodological improvements were made for the current study. First, we conduct econometric analysis of micro data from the Consumer Expenditures Survey (CE), the National Household Travel Survey (NHTS) and the Residential Energy Consumption Survey (RECS) to uncover main drivers of all aspects of consumption in the United States. Variables include demographics (income, household size, race, education), home characteristics (home size, home ownership, structure type, heating fuel), travel behavior (vehicle ownership, commute mode, commute times), geographic variables (population density, weather) and economic data (energy prices). Because those variables are known for each Census Tract and the city overall, we are then able to estimate household expenditures for detailed categories of goods and services for San Francisco at Tract-level. In order to see changes in physical consumption over time, we adjust expenditures using the Consumer Price Index for each product

category. This study also includes detailed models of electricity and natural gas consumption, motor vehicle miles traveled, updated GHG emission factors, and development of a software model that can facilitate future updates and scale for any U.S. geography. San Francisco-specific data were also used to track emissions from residential energy, public transportation, solid waste and wastewater.

This current study builds on methods developed in previous studies for U.S. metropolitan areas (Jones and Kammen, 2011), U.S. zip codes (Jones and Kammen, 2014), the San Francisco Bay Area (Jones, 2015) and the State of California (Jones, Wheeler, Kammen, 2018). An earlier assessment found emissions in San Francisco were roughly 10% lower than the statewide average on a per capita basis (18 vs 19 tCO_{2e}). Total emissions were 14 million metric tons CO_{2e} and 39 tons CO_{2e} per household (18 tCO_{2e} per capita), compared to 44 tCO_{2e} for the typical California household (19 tCO_{2e} per capita). The study also developed estimates at the scale of block groups for the San Francisco Bay Area, finding a 5x difference in consumption-based GHG emissions between the highest and lowest 10% of households, with larger differences in transportation.

The next section contains a brief overview of methods with detailed methods available in the Appendices. The following section provides a summary of results for San Francisco, followed by a discussion on this study's significance, limitations and future research needs, and conclusions including policy recommendations. The methodology and case study presented in this paper should aid in the development of policy and programs directed at community-scale interventions to reduce full consumption-based GHG emissions.

Methodology

The principle methodology used in this study is life cycle assessment (LCA). LCA seeks to identify the major sources of environmental impacts at each stage of product supply chains. This approach is useful for identifying potential interventions at each stage. In our study, "Production" includes all emissions associated with mining, refining, manufacturing, farming, assembly, storage, and business-to-business transport to the factory gate or farm gate. For U.S. products, the production phase accounts for 90% of cradle-to-consumer¹ emissions from food, 95% from services and 60% from goods (Figure 1a). Emissions from transporting products to market are generally quite small relative to full life cycle emissions (Weber and Matthews 2008). In the current study, transporting products to market accounts for about 1% of emissions from food and 4% for goods. The wholesale and retail phases in the United States are also considerably larger for manufactured products (27%) than for food (9%). The use phase is only

¹ Cradle-to-consumer refers to all emissions prior to purchase. This does not include the use phase, such as cooking or in-home energy used to power goods, or the end-of-life disposal phase.

relevant to certain products, such as motor vehicles, major appliances and cooked food. The use phase is a considerably larger portion of emissions in the United States (35%) compared to San Francisco (18%), which benefits from low-carbon sources of electricity, moderate climate and a portfolio of energy and climate policies (Figure 1b). All products have emissions associated with end of life management, such as recycling or disposal, accounting for about 2% of total consumption-based emissions, assuming average U.S. recycling rates and waste management practices.

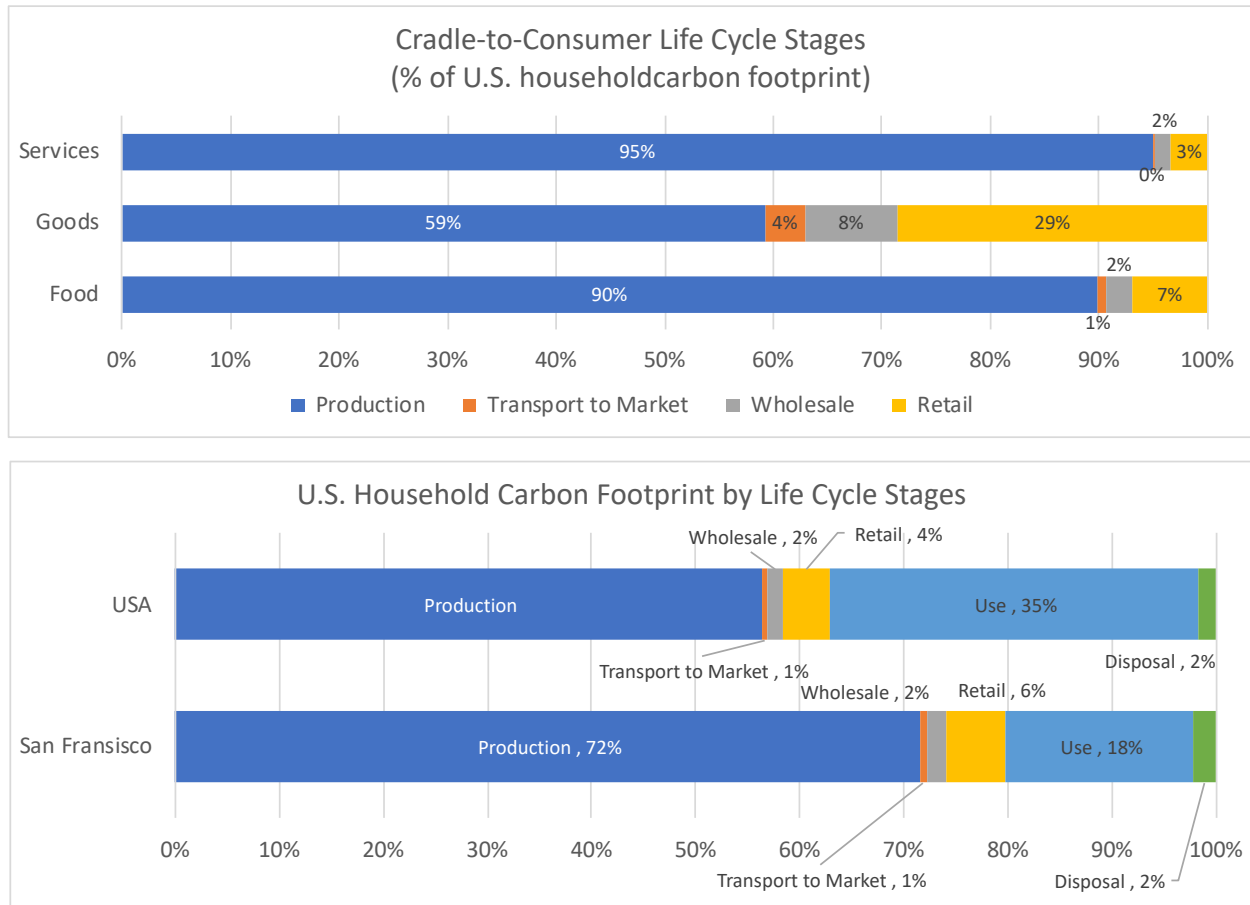


Figure 1a (upper) and 1b (lower). Life cycle stages of US and San Francisco consumption-based GHG inventories. Figure 1a includes all emissions prior to purchase for food, goods and services. Figure 1b includes emissions from all household consumption (transportation, housing, food, goods and services)

U.S. Household Carbon Footprints, 1990 – 2015

Our methodology starts with detailed results from the Consumer Expenditures Survey (CE) for the average U.S. households for the years 1990 to 2015, aggregated into a single file (Appendix 3). The CE, conducted by the Bureau of Labor Statistics (BLS), is the only annual national survey of household consumption in the United States. There are a total of 95 categories and subcategories of expenditures for everything U.S.

households consume, including detailed breakdown of food, utilities, home construction, transportation, household goods and services.

A household carbon footprint refers to the greenhouse gas emissions resulting from the full life cycle of all household expenditures. Simply multiplying expenditures by GHG emission factors for each product category and year would produce the carbon footprint of U.S. households over time; however, to-date there is no comprehensive database of emission factors for food, goods and services dating back to 1990. Our overall approach is to estimate household carbon footprints for the year 2015 and then back-cast emissions to 1990 based on changes in consumption and emissions intensities. The steps to back-cast are as follows: 1) adjust CE household expenditures into 2015 U.S. dollars using the Consumer Price Index (CPI), which is also collected by the Bureau of Labor Statistics, 2) match CE categories to corresponding sectors of the U.S. economy, 3) create emission factors by dividing life cycle emissions from each sector of the U.S. economy in the CEDA environmentally-extended input-output database (Suh 2009) by household expenditures in each consumption category, 4) adjust 2015 CEDA emission factors back in time using decarbonization rates for major sectors of the economy (electricity, transportation, industry, agriculture), 5) substitute household gasoline, electricity, natural gas and other fuels in physical units from sector-specific government data sources (Energy Information Administration and the Federal Highway Administration), 6) apply direct and indirect (well-to-pump) emission factors for fossil fuels and electricity consumed directly by households, and 7) approximate emissions from government expenditures and capital formation as 15% of total emissions by sector (Hertwich and Peters 2006, Weber and Matthews 2008). This methodology allows us to consistently track changes in the quantity of household consumption over time using BLS data and the impact of consumption on emissions using best-available sources. See Appendix 2 for detailed methodology.

San Francisco Household Consumption, 1990 – 2015

Our estimate of national U.S. household carbon footprints relies on accurate assessment of average household consumption in the Consumer Expenditures Survey. In the absence of survey data tracking actual household consumption for cities, our approach is to build econometric models that identify the primary driving factors of each category of consumption, and then apply model results to predict consumption based on variation in those same variables over time and space at local scales. After considerable experimentation with CE public-use microdata (Bureau of Labor Statistics 2019) we find six variables to have the most influence on consumption: 1) household size, 2) income, 3) home size, 4) home ownership, 5) education (college degree or higher) and 6) vehicle ownership.

Each of these variables has a different relative effect on individual categories of consumption. For example, the “food at home” category is largely determined by the number of people in households, regardless of income, education levels, or other potential factors. Each 1% increase in household size from the national average of 2.5 people per household, increases expenditures on food by ~0.5% ($\beta = 0.465$), on average. In contrast, each 1% increase in income, increases expenditures on food by only 0.08% ($\beta = 0.082$). Since San Francisco has 12% fewer people per household than the U.S. overall (2.2 vs. 2.5 people per household), we expect expenditures on food at

home, and corresponding emissions, to be roughly 6% lower ($1 - 2.2 / 2.5 * 0.465$) than the U.S. average, plus much more modest effects from income and other variables in the model. A full summary and discussion of model results is included in Appendix 2

The model form is:

$$\log(\text{Expenditures}_i) = \beta_0 + \beta_1 * \log(\text{INCOME}) + \beta_2 * \log(\text{HHSIZE}) + \beta_3 * \log(\text{ROOMS}) + \beta_4 * \text{OWN} + \beta_5 * \text{DEGREE} + \beta_6 * \text{VEHICLES}$$

Where,

- Expenditures = annual household expenditures for each category i
- INCOME = annual household income before taxes
- HHSIZE = number of people per household
- ROOMS = number of rooms in homes
- OWN = dummy variable for home ownership
- DEGREE = dummy variable for householder achieved college degree or higher
- VEHICLES = number of vehicles driven by household

Household size (HHSIZE) is strongly correlated with expenditures on food at home ($\beta = 0.465$), apparel ($\beta = 0.385$), local public transportation ($\beta = 0.372$), transportation subtotal ($\beta = 0.292$), and housing subtotal ($\beta = 0.204$). Income (INCOME) is strongly correlated with personal insurance and pensions ($\beta = 0.659$), shelter ($\beta = 0.256$), total expenditures ($\beta = 0.248$), air travel ($\beta = 0.242$), vehicle purchases ($\beta = 0.238$), transportation subtotal ($\beta = 0.223$), entertainment services ($\beta = 0.214$), cash contributions ($\beta = 0.211$), apparel ($\beta = 0.203$) and housing subtotal ($\beta = 0.203$). Home size (ROOMS) is strongly correlated with utilities ($\beta = 0.369$), major appliances ($\beta = 0.317$), cash contributions ($\beta = 0.311$), household operations ($\beta = 0.235$), housekeeping supplies ($\beta = 0.235$), and healthcare ($\beta = 0.208$). Home ownership (OWN) is strongly correlated with floor coverings (0.796), major appliances (0.671), healthcare (0.307), vehicle purchases ($\beta = 0.287$), utilities (0.235), furniture ($\beta = 0.223$), and air travel ($\beta = 0.209$). Education (DEGREE) is strongly correlated with education ($\beta = 0.333$), and entertainment services ($\beta = 0.264$). Vehicle ownership (VEHICLES) is associated with expenditures on motor vehicles (gasoline, vehicle purchases, vehicle services) and travel overall ($\beta = 0.189$).

The econometric models, while interesting and policy relevant themselves, also allow us to estimate consumption for every location across the United States. The betas (β) illustrated above tell us how much variation around the mean we can expect for changes in each variable. The American Community Survey (U.S. Census) provides estimates of each variable for every U.S. location down to block group scale. We can therefore estimate consumption for any and all U.S. locations (block groups, tracts, cities, counties, states), based on national average consumption and how much each variable differs from national average values (Jones and Kammen, 2014).

There is considerable variation in the primary drivers of consumption by Census Tract in San Francisco. Annual incomes range from less than \$50,000 to over \$250,000 by neighborhood. While some neighborhoods have less than half a vehicle per household, on average, households south of Golden Gate Park have more than 1.5 vehicles in most neighborhoods and a few tracts have more than the statewide average of two vehicles per household. Households in the southern half of the city also tend to be larger (more people) living in larger homes (more rooms) with higher ownership rates.

There is also considerable variation by education levels with lower rates of college degree attainment in the Southeast and pockets in the downtown area. This variation in the primary socio-economic drivers of consumption affects the spatial distribution of carbon footprints in San Francisco. Some tracts rank high in all primary drivers, for example the Twin Peaks district southwest of the center of the city. We can expect this district to have high carbon footprints relative to neighborhoods that rank low on these drivers, such as the Civic Center district.

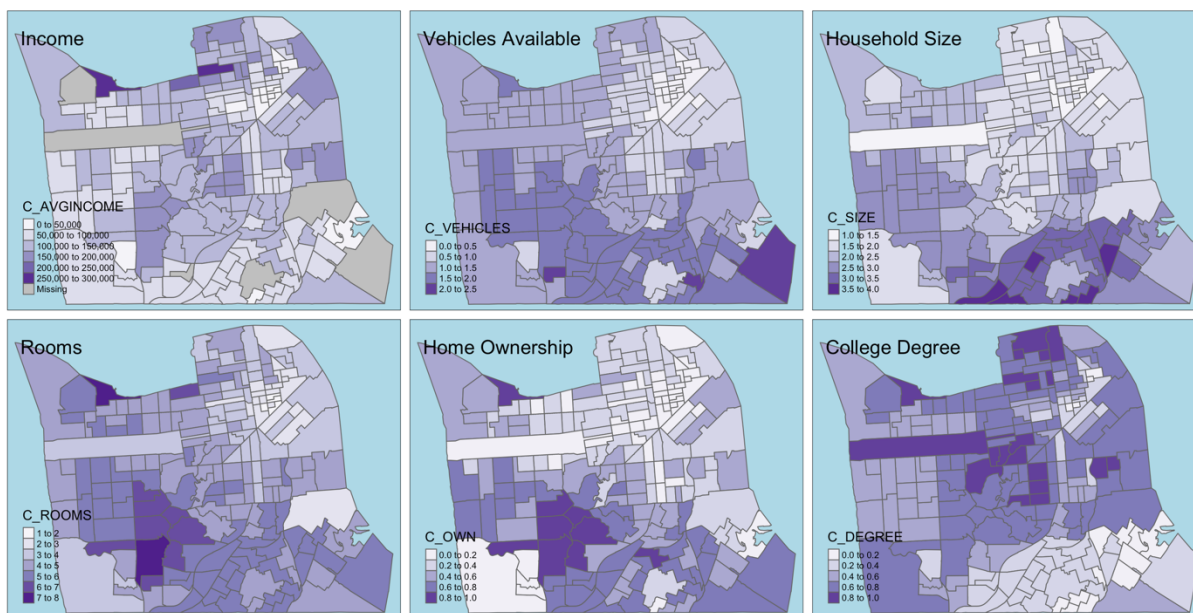


Figure 2. Variation in primary drivers of consumption by Census Tract.

Motor vehicle travel is the single largest source of emissions in California, and for the U.S. overall. We therefore model vehicle travel separately using public use micro data of the National Household Travel Survey. After experimentation with model forms, we found four variables to have the most influence on vehicle miles traveled (VMT), with reasonable goodness of fit (adjusted R-squared = 0.4) compared to published studies. The variables, in order of relative effect, are vehicle ownership, household size, household income and population density. Adding more variables, such as region, travel time to work, number of adults, education, home ownership and race only marginally affected the results and were ultimately excluded from our model. We repeated this process with micro data for four separate NHTS surveys to obtain a time series for the years 1990, 2000, 2009, and 2017.

Household consumption of natural gas and electricity for San Francisco and all other California counties is from the California Energy Commission (CEC, 2020). We further develop econometric models of household energy consumption using the Residential Energy Consumption Survey. Variables include household size, income, size of home, home ownership, structure (single-detached), heating and cooling degree days and energy prices for each heating fuel type (natural gas, electricity, fuel oil and other fuels). Detailed model results are available in Appendix 2. These models allow us to estimate changes in electricity, natural gas and other fuels for each Census tract within San

Francisco based on variation from the San Francisco mean values. A full national map of modeled results is available at: <https://public.tableau.com/profile/cmjones>.

Emissions

We use local data on emissions wherever possible so long as they correspond with a consumption-based approach. See Appendix 2 for calculations and further description of methods discussed below.

Household electricity and natural gas consumption for each California county are from the California Energy Consumption Database (California Energy Commission). Electricity emission factors are from San Francisco's traditional GHG inventory. Fugitive emissions or leaks from the distribution of natural gas was estimated using an assumed leakage rate of 4% natural gas, following the San Francisco traditional GHG inventory (Goodfriend, Pac-Yurrita, and Huertas 2017), when multiplied by the 100-year global warming potentials from the Intergovernmental Panel on Climate Change's Fifth Assessment Report (Edenhofer et al. 2014) leakage increases total direct emission by 47% for natural gas systems.

Emissions from landfilled organic waste and wastewater occur when organic materials decompose and release methane. We use values from San Francisco's traditional GHG inventory, which align closely with national estimates. We assume 50% of emissions in San Francisco's inventory or for residences and the rest are for the commercial sector.

Emissions from public transportation are from the national transit database (Jones and Kammen 2015). Air travel miles are estimated based on income alone (Jones and Kammen 2015) since the impact of other contributing factors (education, home ownership and household size) are small and largely offset each other. Emission factors for fossil fuels (motor vehicle fuels, natural gas and other fuels) are from the U.S. EPA (US Environmental Protection Agency 2020). We multiply direct emissions from EPA by 1.2 to include indirect well-to-pump emissions, consistent with GREET model (Argonne National Laboratory 2013).

All emission factors for food, goods and services are from the CEDA 5 database (Suh 2017) adjusted to CE expenditures. Emissions from home construction are assumed to scale linearly with home size from national average emissions in CEDA. Emission factors are adjusted back in time based on national averages for industry (1% improvement in carbon intensity per year per 2015 US dollar) and agriculture (0.5% annual reduction).

Results

Carbon Footprints in San Francisco

In 1990, the largest source of household carbon footprints (metric tons CO₂e per household) was Transportation (24%),² followed by roughly equal shares of emissions from Housing (21%),³ Services (21%),⁴ and Food (21%)⁵ (Figure 1). The carbon footprint of Goods (13%)⁶ is less than services, which follows since the U.S. is increasingly a service-based economy with considerably more economic activity and spending associated with services than with goods (Suh 2011). By 2015, the order had changed; services (24%) are now the largest source of household carbon footprints, followed closely by Transportation and Food (23% and 21%, respectively), Goods (16%), and Housing (16%). San Francisco, as well as other cities, has traditionally focused on decarbonizing transportation and energy related emissions. With emissions from food, services and goods becoming an increasingly large share of carbon footprints, more opportunities arise for San Francisco to expand upon and enhance strategies to reduce emissions in these areas, especially in their production phase. In San Francisco, emissions from these areas increased from 55% to 61% between 1990 to 2015 (see Figure 1 pie charts). The five major categories are further broken into 24 subcategories, several of which may be further disaggregated, such as “other food,” “other goods” and “other services.” The largest indivisible subcategories include healthcare (3.7 tons), motor vehicle fuel (3.6 tons), air travel (3.2 tons), “eating out,” including take-out and delivery (2.3 tons), natural gas (2.2 tons) and shelter (1.6 tons). See Appendix 5 for detailed results for 95 categories and subcategories for San Francisco from 1990 to 2015, and Appendix 6 for hundreds of individual products and services contained within subcategories.

² Transportation includes: vehicle fuel, vehicle manufacturing, air travel and other household travel

³ Housing includes: electricity, natural gas, other fuels, home construction, water, waste, and other lodging

⁴ Services includes: healthcare, education, entertainment, household operations, financial services, other

⁵ Food includes: meat, dairy, produce, cereals and other food

⁶ Goods includes: apparel, furniture and appliances, and other

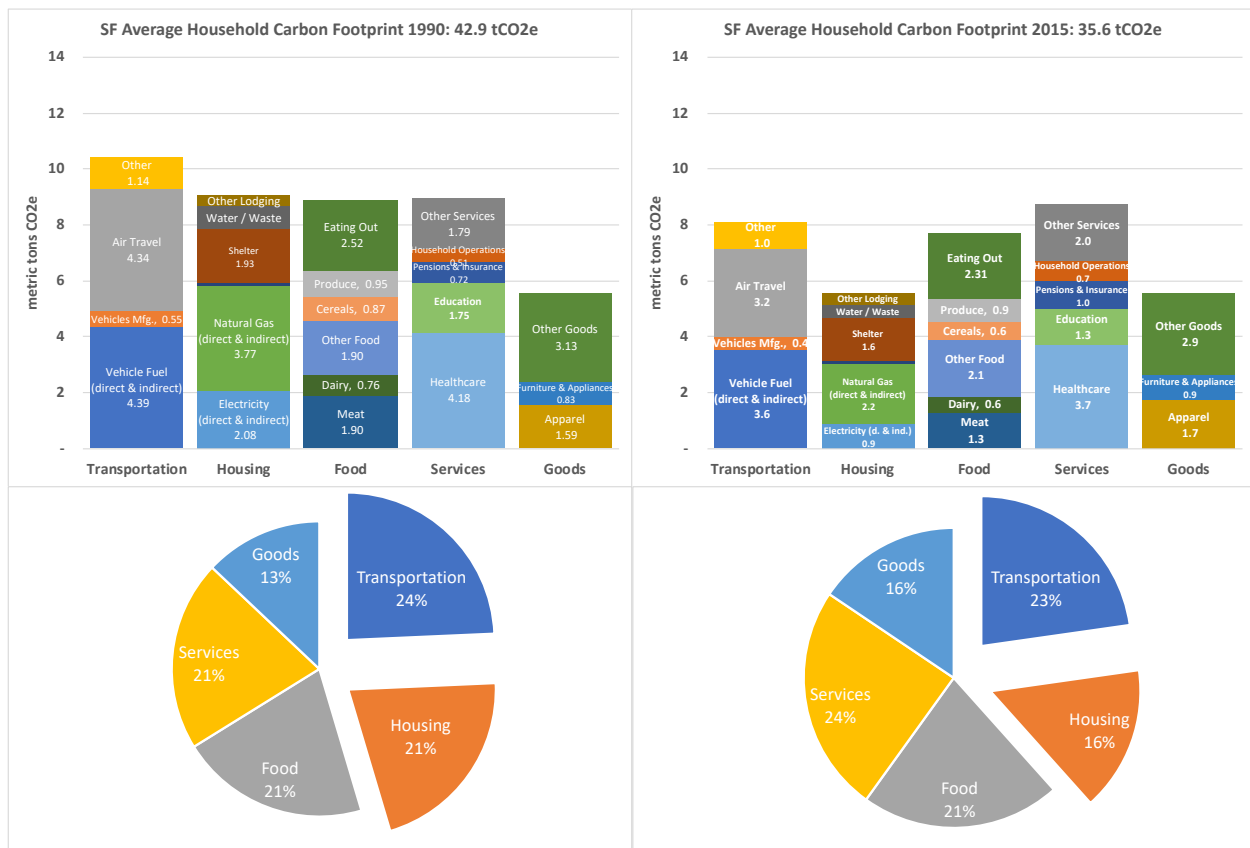


Figure 3. Average San Francisco Household Carbon Footprints in 1990 and 2015

Total average annual household carbon footprints in San Francisco declined from 42.9 to 35.6 metric tons CO₂e per household between 1990 and 2015, a 17% decrease (Figure 3), due primarily to reduction in emissions from electricity, natural gas, transportation and food. While households consistently consumed an average of about 4,000 kWh per year over the study period, GHG emissions from residential electricity declined by 57% due to increased renewables and other low-carbon sources of electricity. In contrast to electricity consumption, which remained steady, natural gas consumption decreased by 43% per household, perhaps due to a combination of increased efficiency and milder winters. Transportation emissions declined by 22% over the same period, with equivalent reductions in motor vehicles and air travel, due primarily to improvements in the fuel economy of motor vehicles and aviation per mile. The carbon footprint of food consumed by San Francisco households decreased by 14% as a result of 0.5% annual efficiency of agriculture and a nation-wide reduction of red meat consumption.

Our research indicates that U.S. industrial and commercial sectors have decarbonized by about 1% per year to produce the same amount of goods and services in recent decades (Appendix 2, section 3). At the same time, incomes in San Francisco have increased, resulting in somewhat more consumption per household. However, as discussed at length in Appendix 1, the effect of income on household consumption has been greatly overstated in previous research, and the actual effect of income on consumption is quite small (less than 0.2% change for each 1% change in income). The net impact of increasing consumption, combined with decarbonization of production is a 15% reduction in the carbon footprint of goods and services consumed by average San

Francisco households. Nevertheless, there are 20% more households in San Francisco in 2015 compared to 1990, so in aggregate, emissions embodied in consumption of all San Francisco households remained relatively flat.

Consumption-based GHG emissions decreased considerably for energy and transportation, yet increasing population entirely offset small reductions in per household carbon footprints from food, goods and services. As a result, the Services category became the largest source of carbon footprints in 2015 (8.7 tCO_{2e}), slightly higher than transportation (8.1 tCO_{2e}) and food (7.7 tCO_{2e}). Housing, which includes electricity, natural gas, home construction, water and waste, was roughly tied with the carbon footprint of all goods consumed by typical S.F. households (both about 5.6 tCO_{2e}).

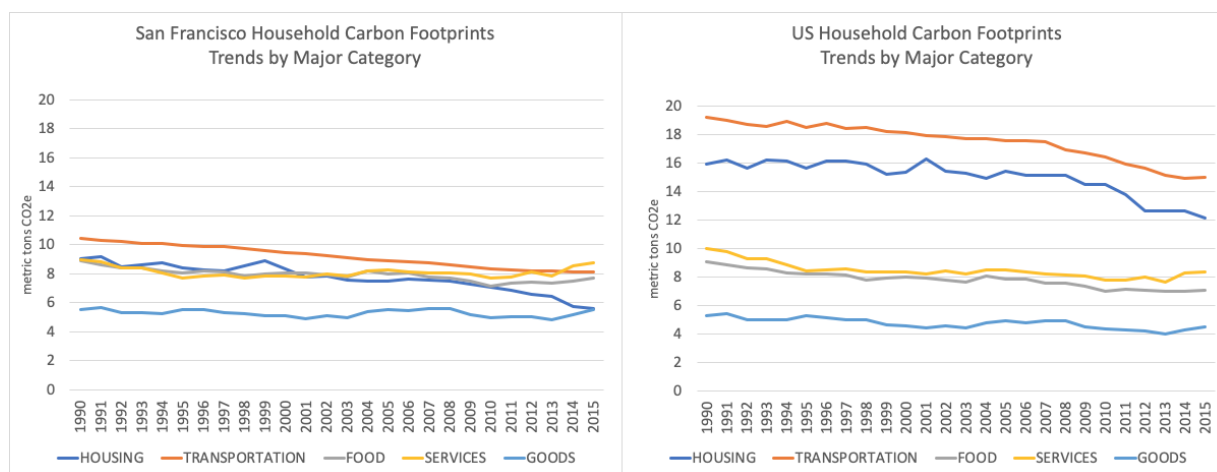


Figure 4. San Francisco and U.S. Household Carbon Footprint Trends by Major Category: 1990 to 2015

The average U.S. household carbon footprint also followed a similar trend to San Francisco's from 1990 to 2015, declining by 21% in the same period, with large reductions from transportation and housing in recent years (Figure 4). Despite high incomes, average household carbon footprints in San Francisco are considerably lower than the U.S. overall due largely to low vehicle ownership, small home size, small household size, low rates of home ownership, moderate climate and relatively low-carbon electricity. San Francisco's 2015 carbon footprint was 35.6 tCO_{2e} per household, which was 21% lower than the national average of 45.3 tCO_{2e} per household.

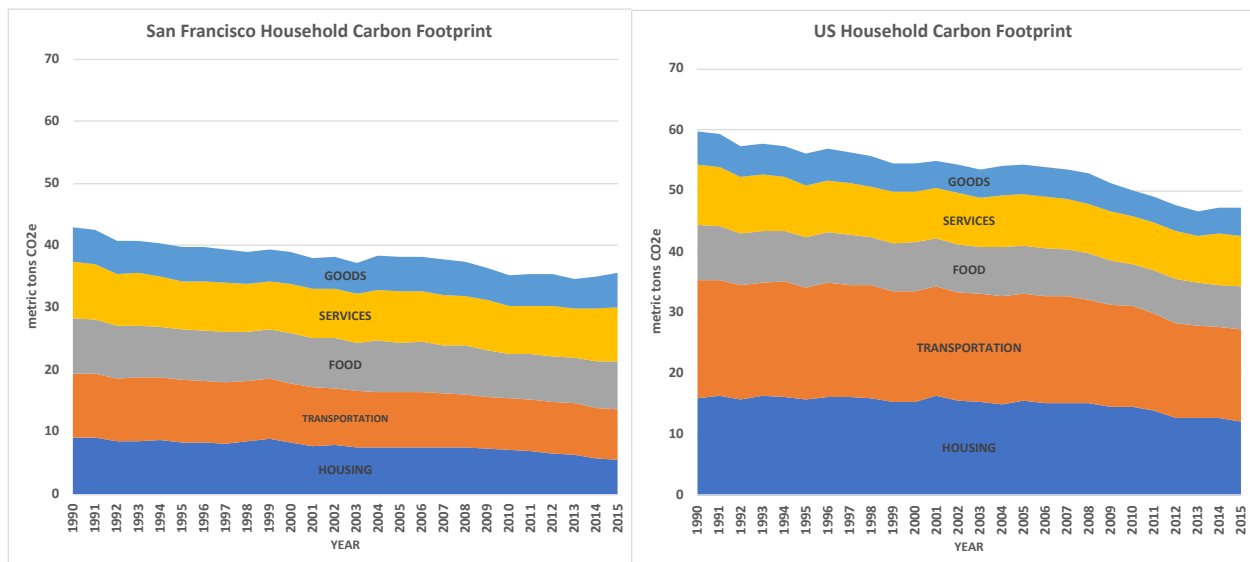


Figure 5. San Francisco vs. U.S. Household Carbon Footprints Trends. Years (x-axis) represent years inventories conducted.

Side-by-side comparison of the U.S. and San Francisco household carbon footprints in 2015 (Figure 6) reveals the carbon impact of San Francisco lifestyles. Transportation and electricity account for the largest differences. San Francisco households produce only 3.6 metric tons of CO₂e from motor vehicle fuel compared to 10 tons for the average U.S. household. This is simply the product of much lower dependency on motor vehicles and fewer miles driven with associated direct and indirect emissions. Emissions from air travel are double the U.S. average in San Francisco due to higher incomes; we have not accounted for the more international demographic composition of San Francisco residents, which likely further contributes to air travel emissions. Electricity is the second largest source of household carbon footprints in the U.S., but only a small contributor to household carbon footprints in San Francisco due to very low carbon-intensity of electricity, moderate climate and relatively low household electricity consumption. San Francisco households also contribute somewhat more emissions from eating out and consumption of goods. The carbon footprint associated with healthcare is slightly lower in San Francisco due to lower household size, but emissions from other services are somewhat higher due to income effects.

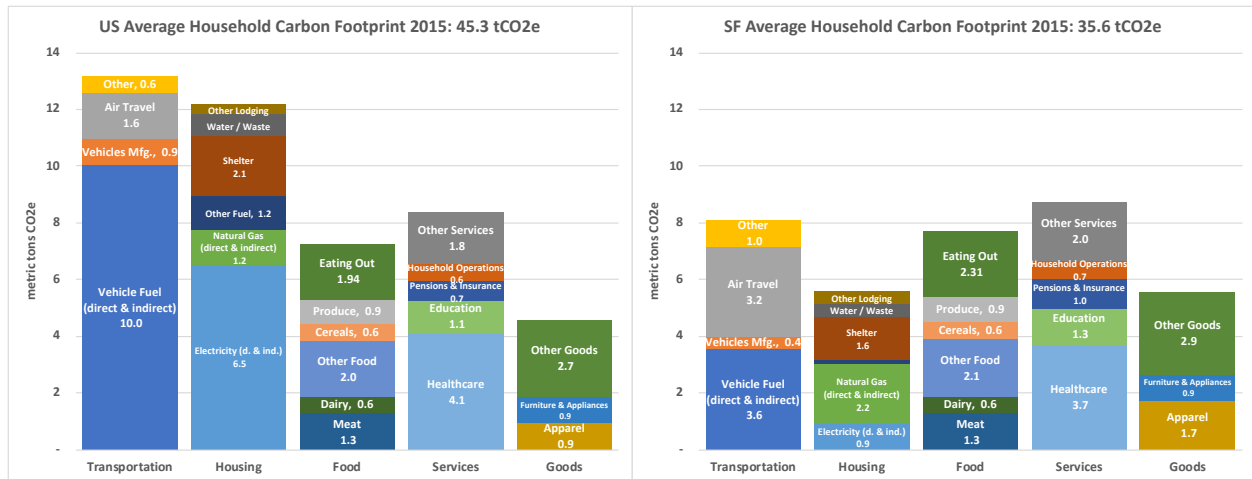


Figure 6. Side-by-side comparison of average U.S. and San Francisco household carbon footprints

Total U.S. emissions are similar in aggregate under both the traditional and consumption-based approaches; the consumption-based approach was less than 10% higher than the traditional inventory in 2015, and previous years were even more similar. The left-hand figure 7 is the official U.S. GHG inventory by sector (U.S. Environmental Protection Agency 2019). The right-hand figure is our estimate of consumption-based GHG emissions for the United States, with emissions allocated to final consumer purchasing demand. Here we include emissions from federal, state and local governments, estimated at 15% of household emissions based on similar studies (Hertwich and Peters 2009); note that the traditional inventory includes only local municipal emissions. Emissions from investment capital (mostly construction) are included in household dairy consumption, consistent with current standards (Södersten, Wood, and Hertwich 2018). The categories of emissions in the traditional and consumption-based approaches are not directly comparable. Emissions from industry, agriculture and commercial sectors, as well as a portion of emissions from transportation (shipping) and electricity in traditional inventories are allocated to food, goods and services through supply chains in the consumption-based approach. Our methodology assumes imports have the same carbon intensity as exports. Future studies could modify carbon intensities of imported goods using a multi-regional input-output model, likely increasing emissions by 10-15% (Weber and Mathews, 2008; Moran, 2019).

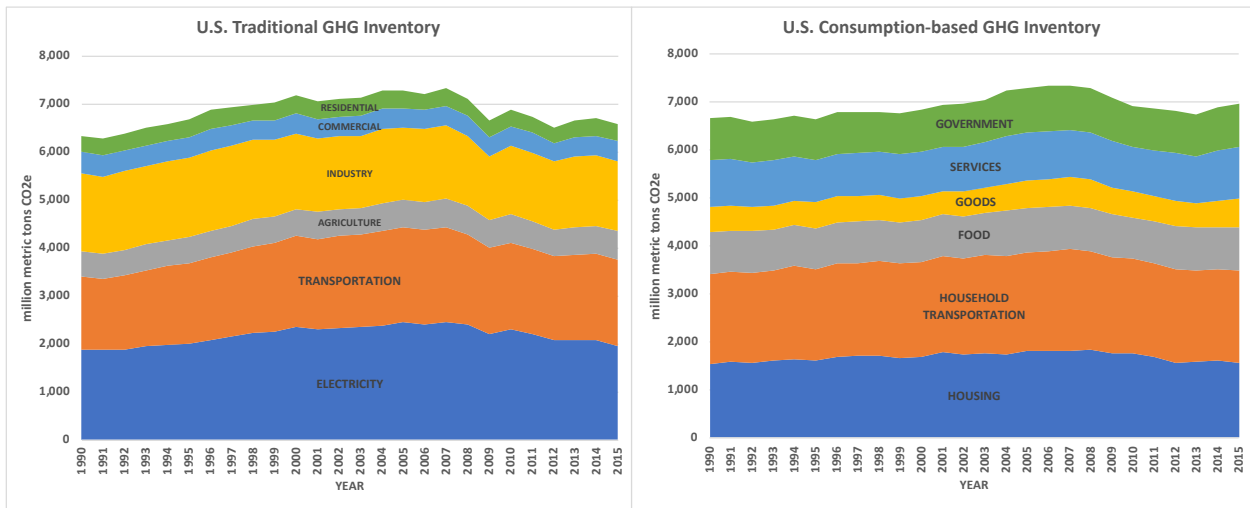


Figure 7. U.S. Territorial versus Consumption-based GHG Inventory

As San Francisco decarbonizes its transportation and buildings sectors, consumption-based emissions are becoming increasingly larger relative to the traditional inventory. In total, the consumption-based inventory is 14.72 million metric tons in 2015, compared to 5.93 million tons under the traditional approach or 2.5 times larger (Figure 7). In 1990 the consumption-based inventory was only 1.6 times larger. Population density across the city explains much of the difference in the inventories. San Francisco does not have much agriculture, industrial activities, or federal operations (military, government administration, etc.). Emissions from San Francisco’s commercial activities are allocated to customers where they live, many of whom live outside of the city’s boundaries.

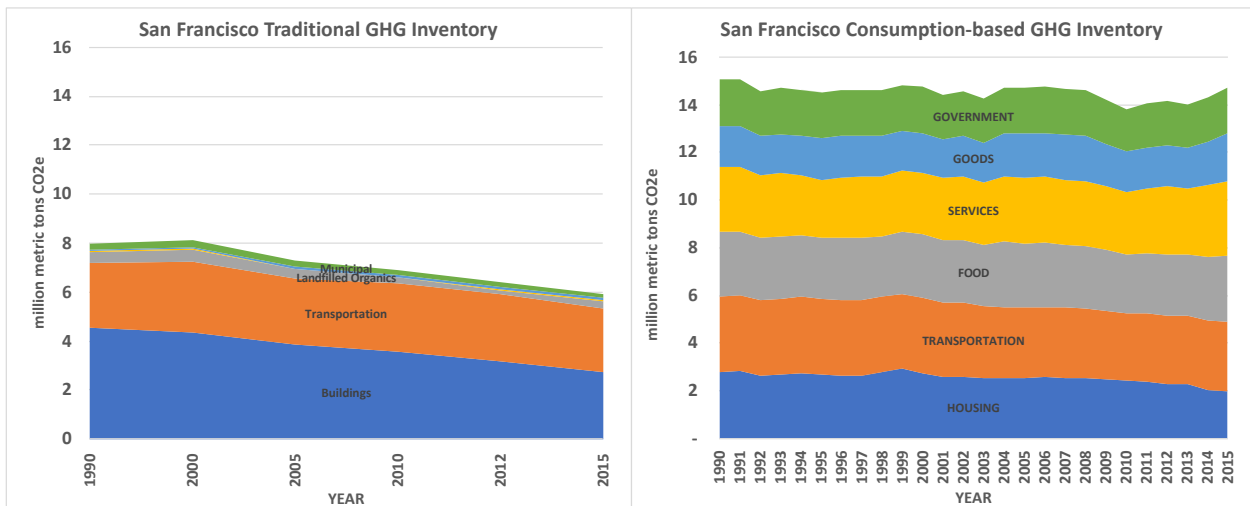


Figure 8. San Francisco Traditional vs. Consumption-based GHG Inventory

There are also important differences in the way transportation emissions are allocated under the approaches. San Francisco’s traditional inventory uses an origin-destination city-induced method approach, which includes in-boundary traffic as well as 50% of trips that either start or end within the boundary of the city and excludes passenger and commercial vehicle pass through traffic. The consumption-based approach considers all travel by San Francisco residents, regardless of where they go inside or outside of the

city’s boundaries, consistent with the “polluter pays” principle. Commercial shipping in the consumption-based approach is embedded in Goods and Services consumed by households whereas commercial travel under San Francisco’s traditional approach is accounted for within the transportation sector using the origin-destination induced methodology describe above. The CBEI also includes indirect emissions from fossil fuels, motor vehicle manufacturing, vehicle repairs, air travel (direct and indirect emission), public transportation and other modes of transportation.

San Francisco’s traditional inventory has decreased considerably since 1990 primarily due to improvements in buildings, including reduction in natural gas usage and decarbonization of the electric grid (Figure 8). Those same improvements are driving down housing emissions in the consumption-based approach. Emissions from services have increased as higher incomes have driven demand. Total emissions from transportation have been roughly equivalent and relatively flat under both assessments, with slow reductions in the CBEI as household vehicles become more fuel efficient. Emissions associated with the full supply chain of consumer goods have increased modestly since 1990, with a recent upward trend from 2010 to 2015 as the economy recovered from the economic recession.

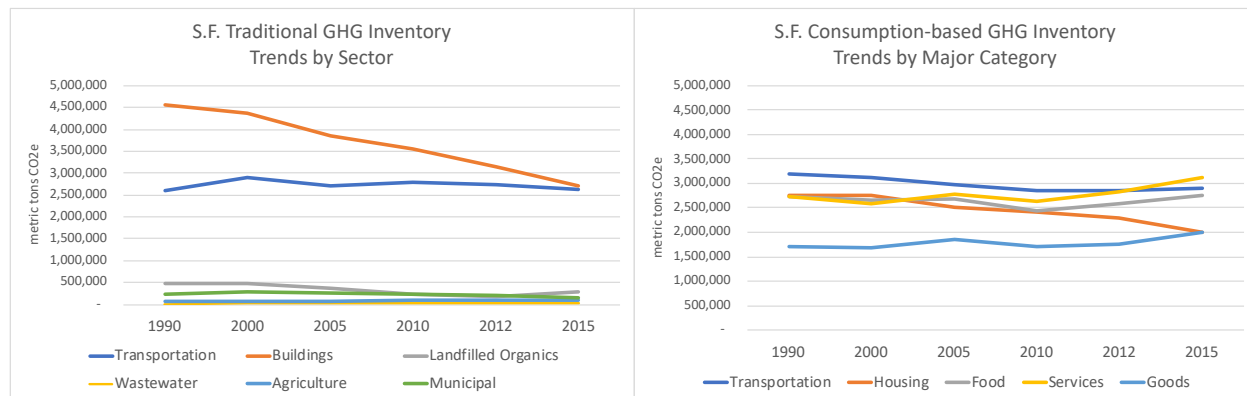


Figure 9. San Francisco Traditional vs. Consumption-based GHG Inventory Trends

Carbon footprints vary dramatically between neighborhoods (census tracts) within San Francisco, based on differences in the key driving factors identified, including household size, home size, income, ownership rates, education level, vehicle ownership, population density, home heating fuels, home structure and other factors) (Figure 9). There is a 4x difference between household carbon footprints in the lowest carbon footprint neighborhoods, located near the financial district, and the highest carbon footprint locations, mostly in the southern half of the city and some high-income neighborhoods near the Presidio. Differences on a per capita basis are lower since high carbon footprint households tend to have more people. While it is important for policymakers to consider carbon footprints of the entire city by product category, it is equally important for policymakers to consider differences in the size and composition of carbon footprints of neighborhoods and residents within them. For example, air travel and motor vehicle emissions are the highest sources of emissions in some neighborhoods (particularly higher income neighborhoods), while food is the largest source of carbon footprints in others (particularly lower-income neighborhoods). The variation between neighborhoods is explained by differences in primary driving factors: vehicle ownership, incomes, household size, home ownership, size of homes and education levels.

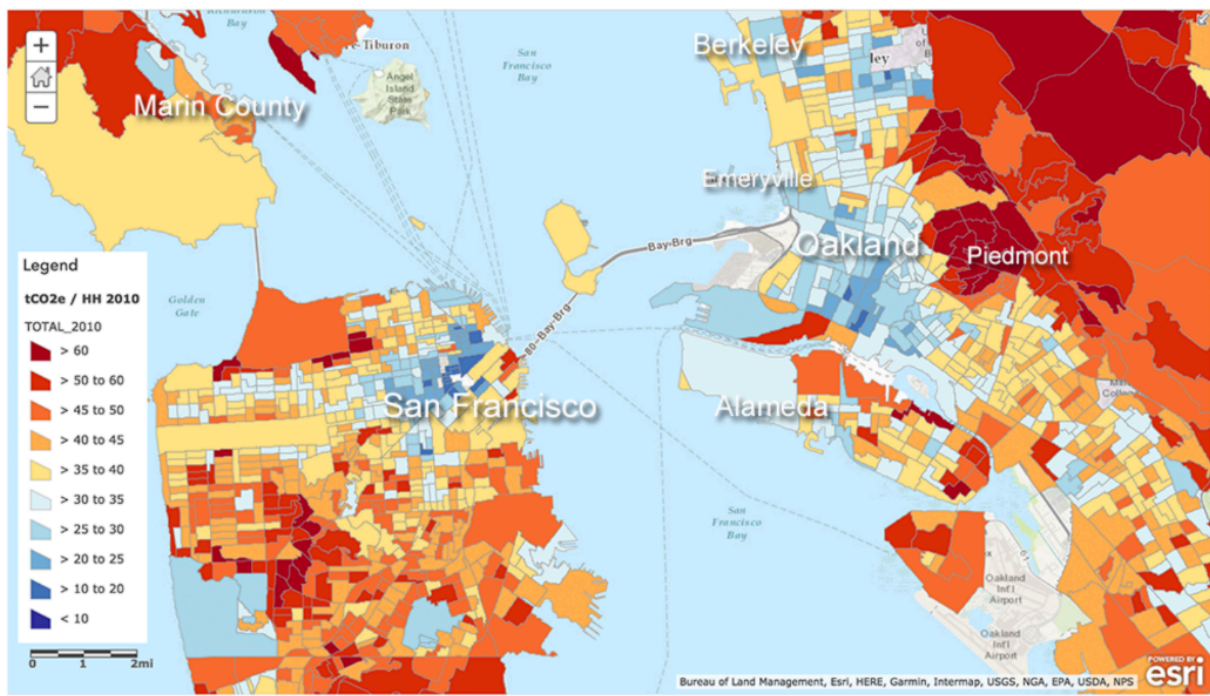


Figure 10. Average household carbon footprints in San Francisco Bay Area: <https://coolclimate.org/scenarios>.

Discussion

Major findings

Despite higher than average incomes, and increased purchasing power in San Francisco since 1990, carbon footprints have declined by 17% since 1990 and are 21% lower than the national average on a per household basis. This conclusion stands in contrast to previous CBEIs performed for San Francisco, which used income alone to estimate carbon footprints. Analysis of the driving factors of emissions and how these change over time and geography greatly improves the accuracy and validity of the consumption-based approach. First, we find income to have an elasticity of only 0.25 for total consumption, and less for most consumer food, goods and services. Second, we find the following variables strongly influence certain consumption categories. Household size (the number of people in households) is the most significant variable influencing consumption of food and apparel. Home size (the number of rooms) and home ownership greatly influence consumption of goods and household services. Education influences consumption associated with social status, including more spending on education, eating out, travel and entertainment. Vehicle ownership, which varies considerably by location, has a large impact on vehicle travel.

This study also finds a rather dramatic shift in the composition of carbon footprints in San Francisco since 1990. After decades of reducing emissions from buildings and transportation (on a per capita basis), consumption of food, goods and services has become an increasingly large share of total household carbon footprints. Once the largest source of household carbon footprints in 1990, Transportation has been outpaced by Services, as the largest source of household carbon footprints today. Transportation and food-related carbon footprints are roughly on par, followed by emissions from household goods. A somewhat surprising finding is U.S. and San Francisco beef consumption per household has decreased by about 25% since 1990 (after triangulating this result with US food and drug administration data). Nonetheless, given high GHG-intensity of beef and dairy, the reduction of beef can still play an important role in reducing the carbon footprint of food. Overall, despite a 17% total reduction in carbon footprints (metric tons CO_{2e} per household) since 1990, total GHG emissions (metric tons CO_{2e}) in the San Francisco have remained relatively flat in absolute terms due to increasing population.

The sources of emissions most within the control of local government appear to be reducing more quickly. In particular, emissions from buildings, both electricity and natural gas, have reduced by 50% per household since 1990. Transportation emissions have decreased by 22% per household, which is considerable considering emissions were already low relative to other California cities and city governments have less control over transportation than buildings. San Francisco has made long and steady progress in decarbonizing the grid and has recently stepped up its commitment with a 100% renewable electricity goal by 2030 and 100% renewable energy goal by 2050. Life cycle emissions embedded in Food, Goods and Services are clearly more difficult to control from local policy. Goods and Services are on an upward trend; however, the shift towards more expenditures on services may be considered a positive step since services are typically less carbon-intensive than goods.

Significance

This study is significant for several reasons. We have updated and advanced previous consumption-based methodologies to include more drivers of consumption other than income, including household size, home ownership, education, size of homes, vehicle ownership and several other important factors affecting vehicle and energy usage. The econometric approach has been underappreciated in recent academic literature, which has identified only two strategies for consumption-based inventories: household surveys and input-output modeling (Appendix 1). We have uncovered major flaws when using these approaches alone. Household surveys are expensive and unable to accurately characterize expenditures on infrequently purchased items, and regional input-output models, e.g., IMPLAN, focus exclusively on the effect of income to allocate expenditures to locations. Our econometric approach is a hybrid methodology that uses the best aspects of surveys and input-output models. Household surveys are used to understand the driving forces of emissions and then local data is used to extrapolate expenditures based on local characteristics. Input-output models are used only for GHG emission factors of food, goods and services. We use local energy data and other local data sources wherever possible to get a more comprehensive and accurate picture of emissions. Transportation is modeled separately, given the high importance of this source of emissions.

Limitations

A key limitation of the consumption-based approach has been the ability to see the effect of policy and to track changes over time. The current approach improves tracking by including more policy-relevant variables, including home size, household size, home ownership, education, income, population density and vehicle ownership. The study also includes local data on energy consumption, carbon-intensity of electricity, water, waste, and public transportation. However, local changes in policy, behavior, infrastructure and most technology are not included in the current approach. If a local policy changed consumption patterns or the carbon intensity of products or services consumed, we would not be able to monitor this with the current methodology; however, additional data could supplement the approach in future studies. For example, a push to reduce meat consumption in school, hospital and workplace cafeterias could contribute to an understanding of changes in local diets.

The current study does not include an estimate of total study error. Ideally, each estimate of consumption and emissions would include uncertainty bounds and analysis of error. Potential sources of error include reporting error in household survey day, sampling error, model error, categorization error and other errors typically associated with input-output models (in this case, the CEDA 5 database). All of these errors are known and could be propagated through formulas in the study in future research. We have also noticed that matching Consumer Expenditures Survey categories with the appropriate corresponding category of the Consumer Price Index is critical for estimating emissions over time.

We also assume the carbon intensity of imported goods to be the same as domestically-produced goods and are not able to track the countries of origin of emissions associated

with local consumption with the current model. This assumption may affect individual products, such as computers, but is unlikely to have a large impact overall since the United States has a large, fairly carbon-intensive production system, with considerable electricity production from coal, similar to many importing countries. Future studies could incorporate a multi-regional input output model to provide better data on the effect of location consumption on international supply chains.

We assume that price corresponds with “value added” economic activity. If San Francisco residents, on average, purchase higher priced goods, then the methodology will linearly scale emissions up with prices. This scaling is appropriate if higher prices are the result of additional economic activity, such as importing products from abroad, but is problematic when prices are artificially raised, such as for branding purposes alone. Conversely, cheaper products will result in lower emissions in the model. Generally, we assume that price differences average out over thousands of households.

Future Research

A number of additional research steps would improve the usefulness of this study. Error propagation and sensitivity analysis would help contextualize uncertainty of the results. An important advantage of the modeled approach is the ability to extend results to any location in the United States; this work is already in progress. Tracking of emissions backwards from 1990 to 2015 could be combined with forecasting efforts (e.g., Jones, Kammen, Wheeler, 2018) to provide policy planning tools with long time horizons. This would allow local governments like San Francisco to more easily set targets based on the emissions reduction potential of each community. Over time, projected years should be replaced with actual results as more data become available. To the extent possible, consumption-based inventories, forecasting and scenario-based analysis should be automated, and made widely available for any location and municipal government to easily include in climate action plans. With fully automated inventories, template climate action plan text could also be generated using data from the tools.

There are several places where additional research would improve the accuracy of the model. The largest sources of emissions justify additional research to validate and improve the results. In particular, large sectors such as healthcare, shelter and education, meat, restaurants and apparel deserve additional scrutiny and research. Data on the fuel economy of vehicles and miles traveled by those vehicles would improve accuracy of motor vehicle emissions, which are the largest source in most U.S. locations. Such data can be collected and analyzed from departments of motor vehicles. The authors currently have a data agreement with the California Department of Motor Vehicles to collect and analyze these data for inclusion in future studies. This would be a significant improvement over current traditional and consumption-based GHG inventory methodologies since data would be highly localized and comprehensive.

As mentioned in the limitations section above, the methodology currently only tracks changes in carbon footprints to the extent national consumption and emissions intensities change, or local data included in the study change (household size, home size, incomes, energy consumption, etc.). It is possible to model the effect of local policy with indicators that could be readily tracked by local government. For example,

emissions from restaurants assume average meals nationally, with average supply chains. Tracking total calories of food sold by different product categories (meat, dairy, produce, cereals, other) in restaurants and schools would greatly aid in estimates of emissions from these establishments and given a better indication of local diets.

There are potential improvements in the core methodology. The current study assumes the carbon intensity of imports is the same as domestically produced goods. A global, multi-regional input-output model would aid in the accuracy of the results, as well as the ability to communicate the global implications of local demand. One novel, and analytically promising way to do this would be to update the household consumption vector in IMPLAN or another input-output model, taking advantage of the best aspects of each methodology.

Another promising development is current work to expand the availability of key environmental indicators for cities and counties in an online platform, allowing community stakeholders to understand and track progress over time. CoolClimate Network partner EcoDataLab project is undertaking just this task. The authors invite local and regional governments and other entities to contribute to this effort and ongoing development of such a platform. Ideally, traditional and consumption-based inventories would be largely automated, allowing staff time to be redirected from data management to the more impactful work of implementation, policy, strategy, and program development as well as in-depth analysis of emission reduction impacts.

Finally, the policy recommendations made herein are only preliminary and deserve considerably more analysis, discussion and vetting before being applied at scale. We have not attempted to quantify the costs/benefits of particular policy options, nor have we explored any of these policies in detail. This is a critical next step for researchers and city staff, in coordination with the full range of citywide stakeholders.

Conclusion

Overview

This study develops a consumption-based greenhouse gas inventory for the City and County of San Francisco for the years 1990 to 2015 assessing production to consumption life cycle GHG emissions. A number of methodological improvements over previous studies make the results more accurate and policy-relevant.

We find average household carbon footprints in San Francisco to be 21% below the national average in 2015, 35.6 vs. 45.3 metric tons CO₂ equivalent per household. Household carbon footprints declined from 42.9 to 35.6 metric tons between 1990 and 2015, a 17% change. The largest source of emissions in 2015 was Services, followed by Transportation, Food, Housing, and Goods product categories. The largest sources of GHG reductions observed were from household electricity, natural gas, motor vehicles, and animal products.

While carbon footprints (emissions per household) have declined, population has increased over the same time period, roughly leveling off total GHG emissions. Our research shows that households with the same income levels have lower carbon footprints living in San Francisco than in other U.S. locations due to lower energy consumption, much less dependency on motor vehicles, smaller home size, and fewer people per household size. Thus, global greenhouse gas emissions are reduced when households move to San Francisco, even as the city's emissions go up.

The research tools and methodologies developed for this study should aid in more accurate assessment of consumption-based GHG emissions inventories for other U.S. locations. One big advantage of the methodology is its applicability and scalability to all U.S. locations. The econometric approach allows the same models to be applied to any location so long as the independent variables are known (e.g., demographic information, home structure, vehicle ownership, geographic information, etc.). This allows the model to be readily applied to any U.S. location and then further refined with local data as needed. The foundation of this work is currently being conducted by CoolClimate Network for all U.S. locations.

Policy Recommendations

The impact of local activities on GHG emissions may be viewed from multiple perspectives, with different implications for local policy. This study presents results from a production to consumption perspective with all global greenhouse gas emissions allocated to final demand, i.e., households and government activities. Traditional inventories, on the other hand, highlight emissions where they physically enter the atmosphere. From this perspective, industrial and commercial activities within San Francisco produce emissions for households both within and outside of the city boundaries. San Francisco's high population density and relative lack of industrial activity result in the consumption-based GHG inventory being 2.5 times larger than the traditional, largely production-based GHG inventory. Given the importance of

consumption-based, life cycle emissions relative to local-only emissions in San Francisco it is important to consider policies and programs that address life cycle impacts, as a complement to traditional, geographic-based interventions.

The two primary sources of emissions measured in the official and traditional geographic based GHG inventory are buildings and transportation. Hence, the City has made considerable emissions reductions of 26% from 1990 to 2015, mainly driven from residential and commercial energy and modest ground transportation (public transit, passenger and commercial vehicles) reductions. In contrast, from 1990 to 2015, total consumption-based emissions (metric tons of CO₂e) have remained relatively flat, and appear to be increasing in recent years while emission per household (metric tons of CO₂e per household) have decreased. Total consumption-based emissions are now 2.5 times larger than the traditional GHG inventory, underscoring the importance of addressing emissions associated with the life cycle of goods and services consumed by San Francisco residents.

Developing policy from consumption-based emissions inventories is a new and emerging field. A recent study (Jones, Wheeler, and Kammen 2018) identified carbon footprint reduction opportunities for all California cities and counties and resulted in the development of an online climate policy decision-support tool for local governments. See: <https://coolclimate.org/scenarios>. The left-hand figure below represents the carbon footprint reduction potential for San Francisco in 2030 from policies within the control of local policy; the right-hand figure is the reduction potential under local control for the entire State of California. According to this previous study, the largest single opportunity identified for local policy in San Francisco was urban infill (e.g., building more housing in already population dense locations), since households with the same income levels living elsewhere in California would have higher carbon footprints. Commercial efficiency (reducing emissions from the Services product category) was identified as the second largest opportunity in San Francisco. This should not be surprising given the relatively large contribution of services (i.e. healthcare, education) in San Francisco carbon footprints. While the city has cut natural gas usage by 40% since 1990, there remains large opportunities to electrify buildings such as with heating with energy efficient heat pumps. Compared to most other cities in California, San Francisco's GHG reduction opportunities from vehicles may be lower relative to other opportunities. Encouraging healthy diets and shifting consumption from carbon-intensive, to less carbon-intensive services and information present the next largest GHG abatement potential. This decision-support tool (currently only available for California) may provide a useful context for identifying policy intervention areas, but it will be important for local governments to engage stakeholders to set appropriate policies and target adoption rates.

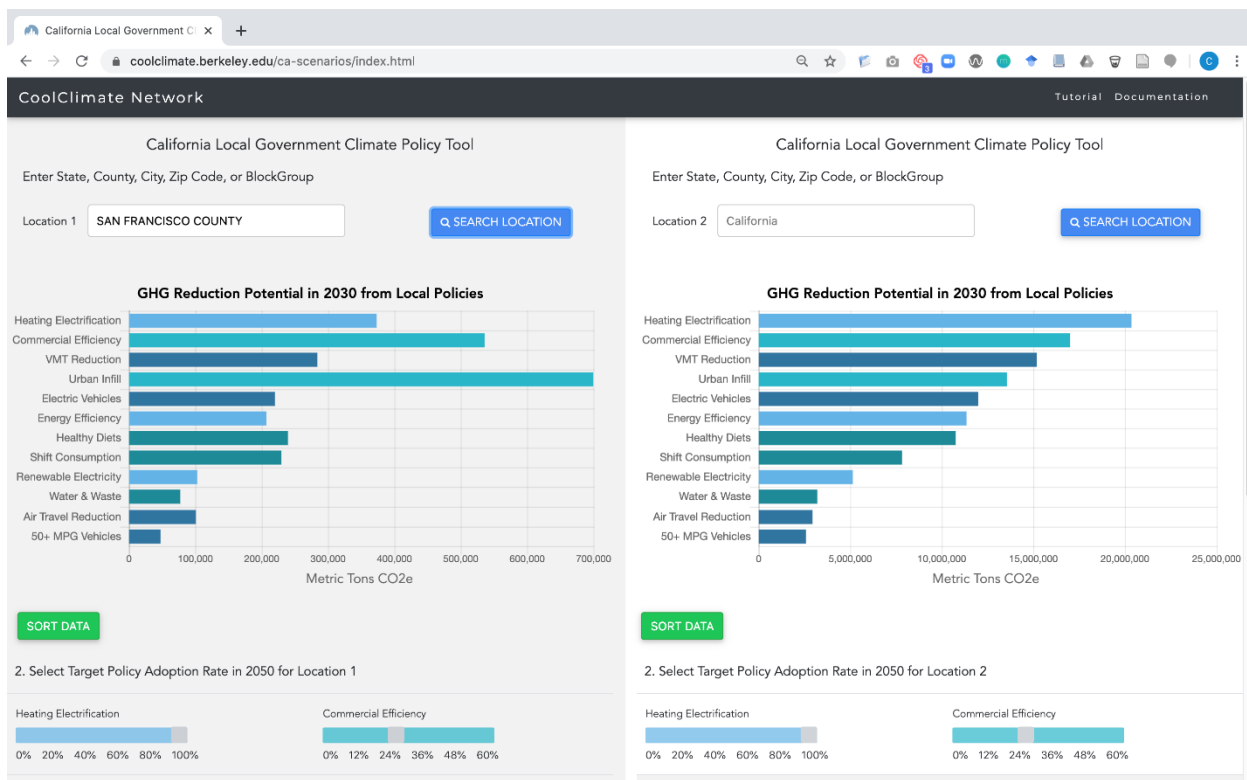


Figure 11. Screenshot from the California Local Government Climate Policy Tool Using Default Target Policy Adoption Rates. This figure does not reflect San Francisco's current policies and programs and should be refined to reflect actual reduction potential projections.

Setting emission reduction targets is an important long-range policy planning tool for local governments that may be codified into law. Using a traditional emissions inventory, local governments typically set targets based on absolute (total) emissions. This approach is limiting because it does not consider the effect of population changes or economic activity over time. The California Air Resources Board ([California Air Resources Board 2017](#)) recommends local governments set absolute targets, per capita targets, and targets based on service populations (residents plus workers). Furthermore, these targets should be in line with statewide objectives of reaching 40% below 1990 levels by 2030 and 80% below by 2050. Setting per capita targets that accommodate increasing population density in low carbon areas such as San Francisco is a key strategy for reducing emissions statewide (Figure 11), yet this densification would increase absolute emissions in these locations. At the same time, emissions inventories may seem to discourage economic growth or increased density if targets are set based on absolute levels. Per household targets may be preferred over per capita targets, since increasing household size (i.e., having more children) would perversely lower per capita emissions. In sum, it may be appropriate to set consumption-based targets on either a per capita or per household basis, and set traditional inventory targets based on service population in addition to absolute targets to help accommodate variations in local demographic and economic conditions.

Outreach and Communication

A significant benefit of a consumption-based inventory is as a messaging tool for the public. The development of carbon footprint profiles helps individuals and households understand the largest contributing factors of their lifestyles. The relative contribution of different emission sources may be surprising. For example, electricity accounts for only about 2% of typical San Francisco carbon footprints while Services total nearly 25%. Consumption-based carbon footprint calculators such as the CoolClimate Calculator, developed with data for this project (<https://coolclimate.org/calculator>), can be leveraged to influence household behavior. Behavior-based programs and tools that engage residents directly in climate action hold even greater potential. A recent competition, the Cool Campus Challenge, engaged 22,000 staff, students and faculty at the University of California to take over 200,000 actions to reduce their carbon footprints by an average of 1 ton each in just over four weeks: <https://coolcampuschallenge.org>.

It is important to recognize that consumption-based policies and programs alone are insufficient to meet local, state, national and global greenhouse gas targets. Households have limited control over greenhouse gases emitted during the production of food, goods and services they consume. Emissions from supply chains are best addressed through national, state, and sometimes local-level policy, such as encouraging greater producer responsibility in product design and life cycle impacts. It is critical that businesses reduce their own supply chain emissions. Making the carbon footprint of products visible to consumer may put pressure on businesses to look inward to reduce the carbon footprint of their supply chains.

While local governments can encourage and promote more climate friendly consumption-habits of residents; those efforts are likely more limited than the greater control governments have over the carbon-intensity of building energy sources, transportation infrastructure, material discard management (e.g., reduce, reuse, recycling, and composting) as well as local policies, programs, and incentives. In order to meet more aggressive climate targets, it will be essential for local governments to engage individuals at all spheres of influence, in their households, places of work, through peer networks, community-based organizations, and through advocacy to change behavior and create lasting habits that impact emissions well beyond geographical boundaries. The resources developed in this study should be helpful to engage households and the broader community to make more informed decisions about their consumption and inform needed policy opportunities to facilitate greater responsibility for producers and consumers to reduce their life cycle impact on the climate.

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Appendix 1: CBEI Methodological Improvements

Three basic approaches have been used by researchers to estimate consumption at subnational scales (J Heinonen, J Ottelin, S Ala-Mantila, T Wiedmann 2020): household surveys, input-output models and econometric models. Since it is not feasible to track every dollar households spend, an estimation approach is required. Below we discuss the major strengths and weaknesses of each approach and present the econometrics methodology used in the current study.

1. Household Surveys

In order for a consumption-based inventory to be policy-relevant it is important to be able to track the impact of policies on consumption and household carbon footprints over time. At first glance, it may appear that collecting expenditures data from a sample of households would be an ideal methodology to track household expenditures over time. In theory, a sample of 400 hundred subjects can produce results that are reliable within a margin of error of +/- 5% with 95% confidence. Any increase or decrease in consumption greater than 5% would be detectable with high confidence with a perfect survey. Unfortunately, household surveys are far from perfect, and in fact, suffer from several fundamental flaws that make them practically infeasible for most cities and counties.

The most important limitation is non-response error. Unlike opinion surveys, in which all subjects may have an opinion about a particular topic, many household expenditures are infrequent or much less common for certain demographic groups. For example, fewer than 50% of Americans fly in any given year, and lower income households fly much less frequently. Expenditures surveys rarely require respondents to recall (through surveys) or track (through diaries) expenditures beyond two or three months in total. Therefore, the total sample of households who purchased air travel in those few months may be quite small. Other expenditures, such as flooring or new cars are purchased by even fewer respondents and less frequently. For these categories of consumption, the majority of respondents may not report any expenditures for that period even though they do sometimes purchase those items. While some may make monthly payments on these items, and thus be recorded, others pay for these expenditures in one-time payments. Analysis of survey results reveals that many categories of consumption have mostly zero values, and the true value is not represented. This leads to sampling error that can be considerably larger than changes in spending over time, even when aggregating many expenditures into large categories.

The Bureau of Economic Analysis tracks a sample of about 2,000 San Francisco Bay Area households every year through the Consumer Expenditures Survey (CE). Figure A1 1 compares results for the two largest categories of expenditures, Apparel and Services, and Furnishings and Equipment for the 5-county SF Bay Area CE subsample (n = 2,000) and for the full US sample (n = 30,000). Apparel, an item which is purchased relatively infrequently has a sampling error of +/- 47% in the San Francisco Bay Area. While mean expenditures on Apparel (in 2015 USD) increased by 33% from 1990 to 2005, we cannot say with 95% confidence that expenditures did not, in fact, decrease during that timeframe due to the large margin of error. In contrast, expenditures on Apparel and Services in the full US sample increased by only 20% between 1990 and

2005, which is a statistically significant change. Similarly, we cannot say a 75% increase in Furniture and Equipment is a statistically significant increase in consumption in the SF Bay Area, while even a 10% increase in the US is significant. In short, a sample of ~2,000 SF Bay Area households is insufficient to track changes over time due to the infrequency of many purchases. Increasing the significance to the level of the US sample would require a tenfold increase in the population sample, with a corresponding increase in cost.

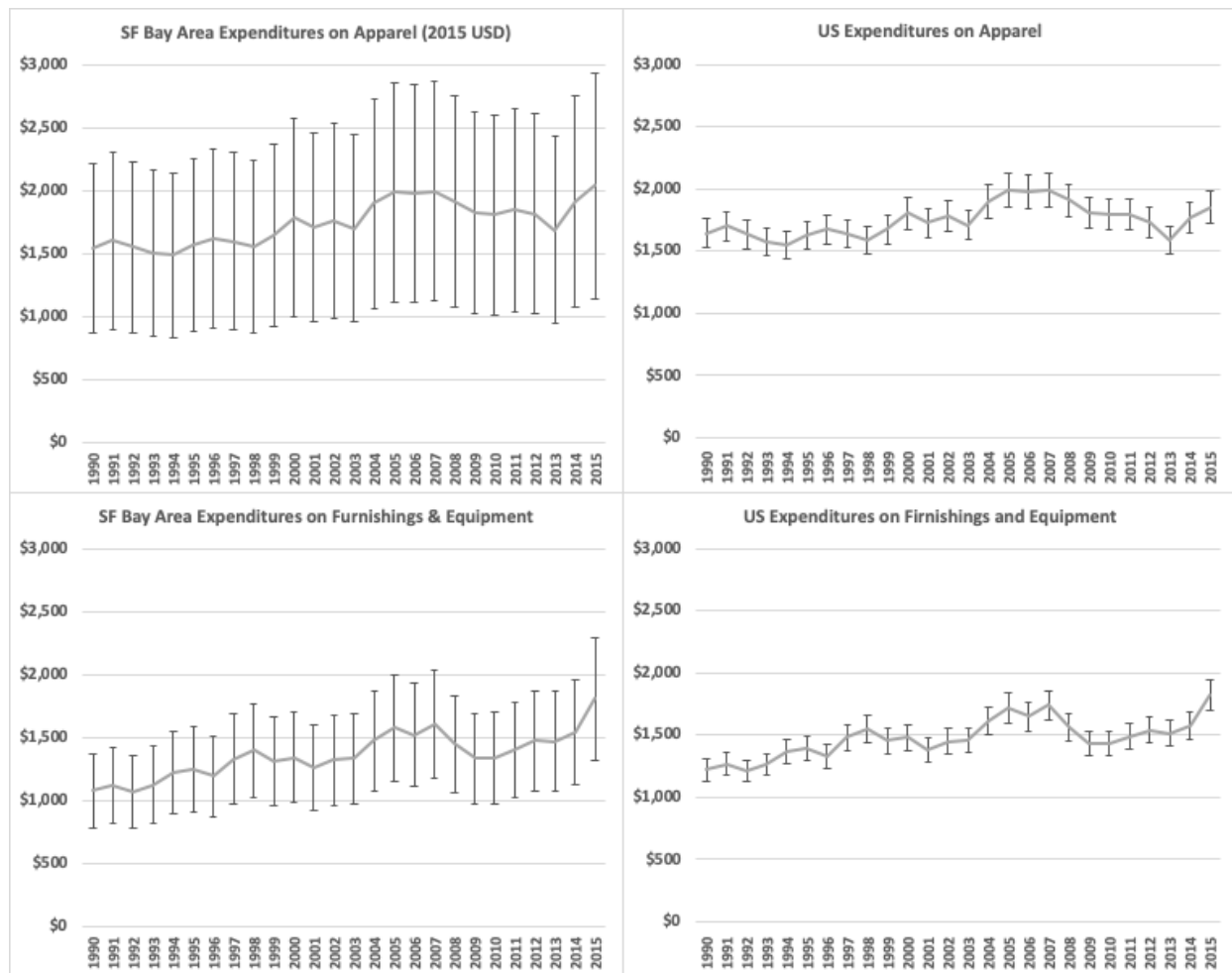


Figure A1 1. Comparison of standard error in San Francisco Bay Area subsample versus the full U.S. Consumer Expenditures Survey

Consumer Expenditures Surveys are also more expensive than most surveys due to their complexity. Since households are not likely to recall individual purchases over long periods of time, the U.S. Bureau of Economic Analysis complements a household survey, with daily diaries for its Consumer Expenditures Survey. Subjects must be trained to log each expenditure they make over a designated period of time, usually several weeks throughout the year. This is necessary to accurately assess consumption of daily expenditures, but increases cost considerably. The total cost of the US CEX is \$1.7 million, or \$248 per respondents. At this rate, a sample of 4000, which is still insufficient to track changes over time for many product categories, would cost \$1,000,000. Cost and non-response error are in addition to other well-known limitations of surveys, such as survey error, response error, non-normal distributions, response bias and others.

In short, while it is tempting to use the San Francisco Bay Area subsample of the U.S. Consumer Expenditures Survey, after review of the data and modeling changes over time we have determined that it is infeasible to use local household survey data to track consumption and emissions over time for San Francisco, or any U.S. city or county for that matter.

2. Input-Output Models

According to the most recent 2008 CBEI, total consumption-based emissions were roughly three times larger than the traditional GHG inventory (21.7 vs. 8.5 million metric tons CO₂e) and San Francisco's emissions were 24% larger than California on a per capita basis (28.3 vs. 22.8 tCO₂e per person). Given San Francisco's high population density, which tends to correspond with relatively low carbon footprints (Jones and Kammen, 2014) this is a surprising finding.

San Francisco was one of the first local governments to develop a consumption-based GHG inventory. Two previous CBEIs were conducted by Stockholm Environment Institute (SEI) using an environmentally-extended input-output model (EIO-LCA) to estimate emissions within and outside of San Francisco's geographic borders. EIO-LCA builds on national input-output tables that track flows of expenditures to and from each sector of the economy. Adding environmental data to each sector allows researchers to track flows of emissions through complete product supply chains and develop intensities per dollar of sector output.

The economic input-output model, IMPLAN, used in the previous CBEI, was designed to track economic flows by sector between U.S. counties. This approach is ideal for tracking in-boundary and trans-boundary emissions associated with each economic sector; however, the household consumption vector in IMPLAN is scaled to San Francisco and other geographies based on income alone (SEI 2008, p.27). This approach fails to recognize that households at different incomes have very different demographic characteristics, home sizes, locations and other factors which contribute to different patterns of consumption and emissions. Another study for the S.F. Bay Area (Jones and Kammen, 2015) used income and household size to allocate emissions of goods and services (but not food, transportation or energy) to Bay Area Census block groups. However, other known factors contribute to household consumption such as home size, home ownership, education, vehicle ownership and other potential model variables. An accurate assessment of these factors is critical to improving CBEIs.

The 2008 San Francisco CBEI, conducted by Stockholm Environment Institute, estimated total emissions in San Francisco to be 21 million metric tons (MMT CO₂e) of which 18 MMT CO₂ are from households or 23 tCO₂e per capita. This corresponds to 24% higher per capita carbon footprint than the Californian average. "Appliances," which includes direct and indirect energy, were 20% lower in San Francisco than the California averages, consistent with traditional GHG inventories. "Vehicles," which includes life cycle emissions from motor vehicle travel, were the same in San Francisco as California in the 2008 CBEI. This result may seem curious since San Franciscans own 50% fewer vehicles per household and only 39% commute by motor vehicle. Here it is important to understand an important nuance of the 2008 CBEI methodology. The

study adopts results from the traditional inventory, which counts 50% of vehicle trips that start and end in San Francisco and allocates those to San Francisco households. Since local households do not demand vehicle travel from outside employees or visitors to San Francisco, this approach is not consistent with the methodology of allocating emissions to final demand.

Category	California	San.Francisco	SF.vs.CA
Appliances	3.400	2.700	0.800
Vehicles	4.300	4.300	1.000
Food.And.Beverages	3.200	5.500	1.700
Services	2.200	2.600	1.200
Construction	1.600	1.800	1.100
Electronics	1.400	1.400	1.000
Healthcare	1.300	1.900	1.500
Transportation.Services	0.900	2.400	2.600
Other	4.500	5.700	1.300
Total	22.810	28.320	1.240

Figure A1 2. San Francisco versus California CBEI in SEI 2008 study

Perhaps most surprising, emissions from Food, Goods and Services in the 2008 CBEI were estimated to be 41% higher than the California average exclusively due to the effect of higher incomes in San Francisco. Food alone was over estimated at 70% higher than average. A major problem of the income-only approach is households of different income levels have different characteristics, which influence spending habits. Those important characteristics, such as household size, are discussed below. According to the Consumer Expenditures Survey, the top 10% highest income earners spend roughly four times as much on food as the lowest decile; yet only twice as much on a per capita basis. Clearly households at the highest income levels are not eating 4x the amount of food...they simply have more people per household. As noted in a previous study, households at different income levels eat the same number of calories of each major food category (Jones and Kammen 2011), so prices play an important role in expenditures.

3. Econometrics

A third, less well-understood modeled approach demonstrated in this project, overcomes several of the largest limitations of the other approaches. The modeled approach uses national surveys to get an accurate assessment of household expenditures, and then uses econometric analysis of survey results to understand the causes of variation between households based on economic, demographic, geographic and physical characteristics of households down to neighborhood scales. The full methodology is detailed in Appendix 2 below.

Appendix 2: Detailed Methodology

1. Expenditures

1.1. Table of Consumer Expenditures from 1990 to 2015

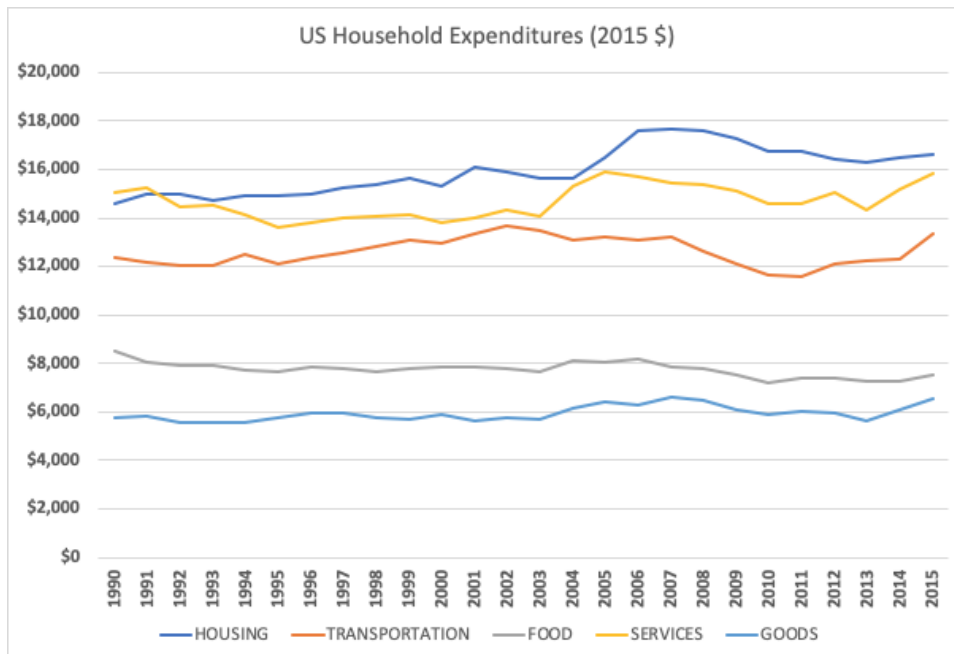
The U.S. Consumer Expenditures Survey (CE), conducted annually by the Bureau of Labor Statistics (BLS), provides detailed data on U.S. consumer spending, in addition to demographic information and other household and home characteristics. BLS has conducted the survey annually since 1980, with earlier surveys dating back to 1888. It is the most comprehensive assessment of U.S. household consumer spending. The open-source data are used extensively in academic and professional research, as well as for government statistical purposes, including the Consumer Price Index. The survey consists of an Interview Survey, for larger and less frequent purchases, and a Diary Survey to track smaller and more frequent purchases. The combined results are published in tables on the BLS website, and micro data are available for download.

The first step of our methodology was to combine summary tables of average annual household expenditures, consisting of 26 major product categories and dozens of minor categories, for the years 1990 to 2015. The product categories have remained consistent during this entire 25-year period. The table is presented in Appendix 3. U.S. households spent an average of two times more overall in current (un-adjusted) US dollars, with the largest increase in education (3.25 times more spending in 2015 vs. 1990), and the lowest change in tobacco and related products (3% increase).

1.2 Convert Table of Expenditures to 2015 USD

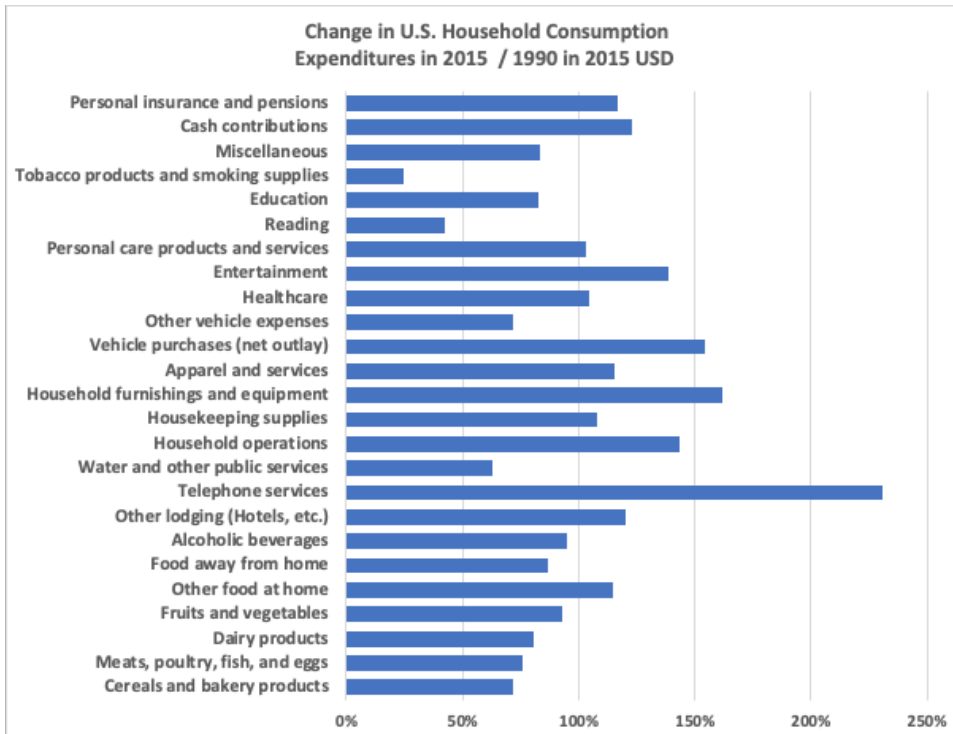
In order to show changes in consumption over time, we converted all expenditures to 2015 US Dollars using the Consumer Price Index. There was an identical one-to-one match for most major product categories. For categories without a direct match, we used a larger product category. We present the combined CPI data set in Appendix 4. Prices increased an average of 70% over the 25 years, with the largest increase in health care (270% increase) and the smallest change (0%) for apparel.

Trends in consumption fluctuate on an annual basis, but long-term trends for major categories of consumption are apparent (Figure A2 1). Food (meat, vegetables/fruits, cereals, etc.) was the only category that decreased, with a total decline of 13% from 1990 to 2015. (See discussion below) Household consumption of goods (furniture, appliances, clothing, other goods...) increased by 21% and housing increased by 16%. Services remained roughly flat, with up to 15% fluctuation over time. Transportation (gasoline, motor vehicles, vehicles, air travel, public transportation...) declined during the recession years, starting in 2008, but began recovering around 2012. The relative contribution of large categories of expenditures stayed constant during the 25 years, with Housing, Transportation, Food, Services and Goods, descending in that order.



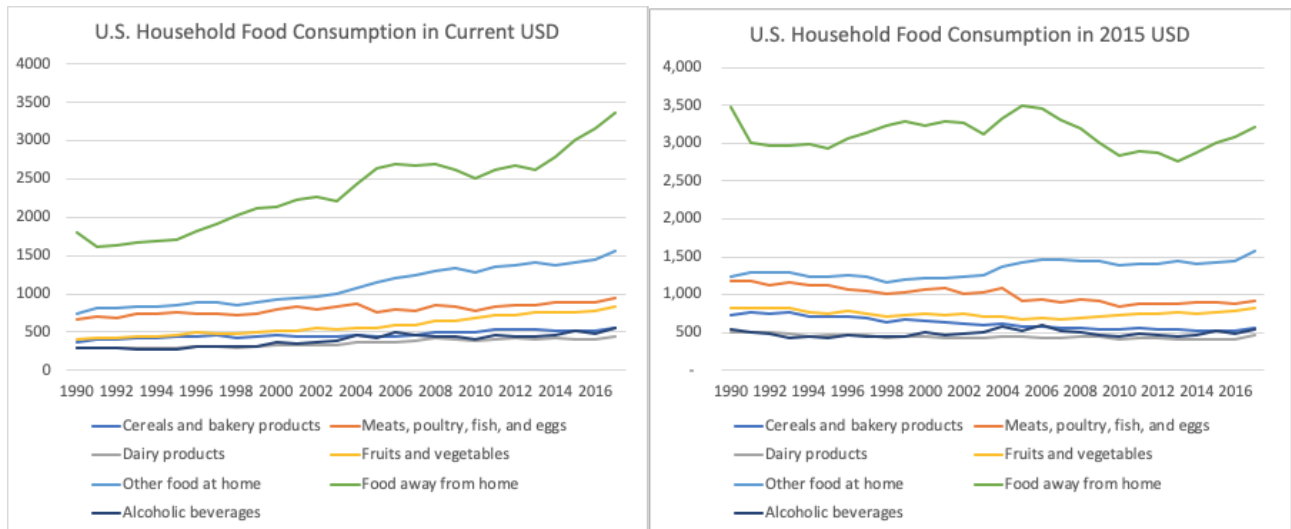
A2 1. Major categories of consumption in the U.S. Consumer Expenditures Survey, 1990 to 2015

Larger changes can be seen in some smaller product categories, ranging from a 75% and 85% decline in tobacco products and floor coverings, respectively, to a 230% increase in telephone service. Figure A2 2 compares the change in consumption in 2015 USD for all major categories of US household consumption; see Appendix 5 for product descriptions. Values less than 1 indicate a decrease in consumption; 100% indicates no change in consumption and 200% indicates a doubling of consumption. Consumption of most goods and services increased over this time period, with the largest increases in telephone service, household furnishings, motor vehicles and entertainment. The total amount of healthcare, clothing and personal care products and services remained about the same. As discussed above, consumption of food decreased, except for other food at home. Households spent about 50% less on tobacco products and reading. We have not included the margin of error in these figures, which tends to be <5% for large items and quite large for infrequently purchased items, such as floor coverings.



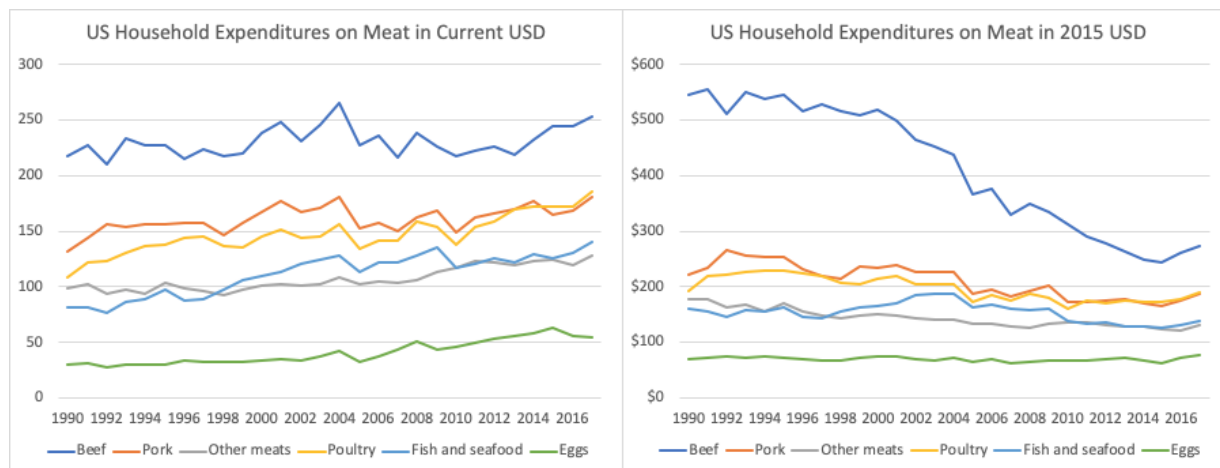
A2 2. Trends in U.S. household consumption in 2015 USD, percentage change (2015 / 1990). Showing trends in fixed 2015 values shows the trend in consumption in physical units.

Food deserves special consideration given the relatively large contribution to greenhouse gas emissions, which is driven largely by methane and nitrous oxide emissions from agriculture and animal products. There was a 13% decrease in total food consumed at home and away from home in real 2015 USD. During the same period, household size decreased by ~5%, from 2.6 to 2.5 persons per household, explaining some of the change. Around the year 2004, there was a sudden and pervasive shift away from Meat toward Other food at home, both in current and constant dollars.



A2 3. Major categories of U.S. food consumption in current vs 2015 USD

While purchasing dollars spent on beef remained relatively flat in constant 2015 USD, quantity of actual beef consumed (in pounds) decreased by more than 50% from 2000 to 2015 in current 2015 USD. For example, the change in consumption was almost entirely driven by change in prices for beef, as reported by BLS.



A2 4. U.S. household expenditures on meat in current vs. 2015 USD

We contacted BLS to get more specific data on beef sub-categories in the Consumer Expenditures Survey (CE) and the Consumer Price Index (CPI-U) and matched up each sub-category on a one-to-one basis. According to BLS data, US households consumed 101.3 pounds of beef in 1998 and only 51.5 pounds in 2017, roughly 50% reduction. Households consumed about 50% less of all cuts of beef during this period. There was a small shift away from ground beef toward more expensive steaks.

Table A2 1. Change in raw beef consumption, 1998 to 2017

Item	1998				2017			
	Expenditures	Cost per Pound	Pounds per HH	Percentage	Expenditures	Cost Per Pound	Pounds per HH	Percentage
Beef*	\$ 218	\$ 2.55	101.3	100%	\$ 253.39	\$ 5.40	51.5	100%
Ground beef*	\$ 79	\$ 1.41	56.0	55%	\$ 95.16	\$ 3.64	26.1	51%
Roast*	\$ 38	\$ 2.66	14.4	14%	\$ 37.97	\$ 5.29	7.2	14%
Steak*	\$ 83	\$ 3.66	22.6	22%	\$ 98.13	\$ 7.34	13.4	26%
Other beef*	\$ 18	\$ 2.20	8.3	8%	\$ 22.14	\$ 4.59	4.8	9%

If we are to believe BLS data on face value, total household consumption of beef (in pounds) reduced by 55% as the prices increased by 250% from 1990 to 2015. Households spent 12% more on beef in current dollars, but 55% less in constant 2015 USD.

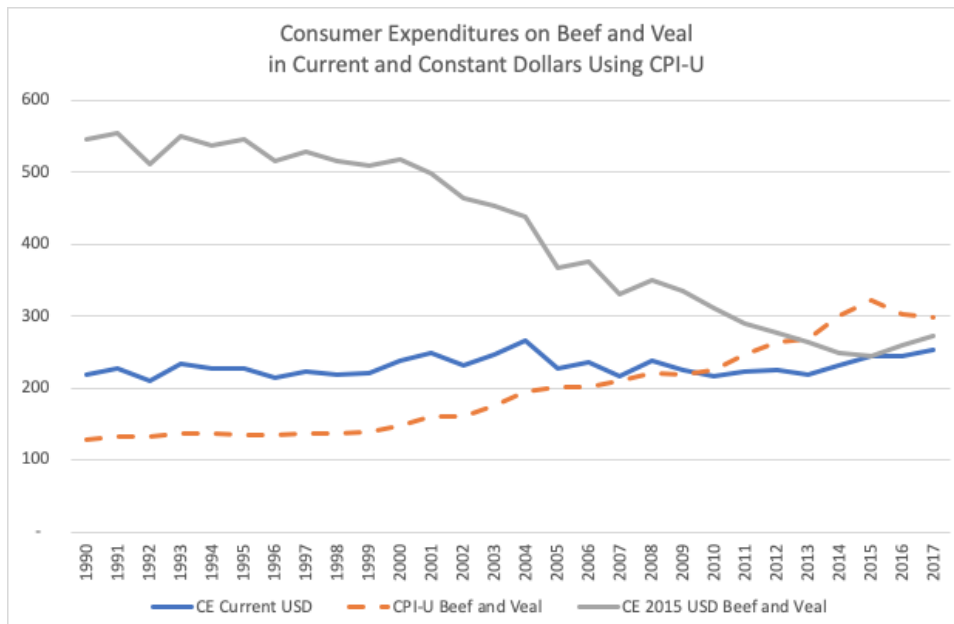


Figure A2 5. Consumer expenditures on Beef and Veal in current and 2015 USD. Y-axis is a unitless index, starting at 121 for CPI-U and Y-axis is in \$ for CE Current USD and CE 2015 USD Beef and Veal

This does not match well with [USDA](#) data, which shows only a 15% decreased in per capita beef consumption (also in pounds), with a commensurate increase in poultry during this period. One possible explanation is BLS changed the categorization of either frozen or processed beef to “Other food at home;” however, BLS experts report being unaware of such a change. While consumption of “Beef” decreased by \$272 per household, “Other miscellaneous foods” increased by \$252. This is only speculation at this point and would need to be either confirmed or disputed by BLS. Until such time, we assume BLS data to be accurate and show a decrease in beef consumption and a similar increase in “Other food at home.”

2. GHG Emissions of Food, Goods and Services using the Input-Output Model CEDA

Environmentally-extended input-output models are frequently used to estimate greenhouse gas emissions and other environmental and social indicators for national economies. Input-output tables are prepared by the U.S. Bureau of Economic Analysis (BEA) to track financial flows between all sectors of the U.S. economy. These are the official government data to estimate gross domestic product and to calculate changes in economic output of different sectors. They are also used to model how changes in economic output from one sector affects all other sectors of the economy directly, and indirectly through supply chains. Environmentally-extended input-output models assign GHG emissions and other environmental indicators to each sector and thus track flows of these indicators through the economy to final demand. The Comprehensive Environmental Data Archive (CEDA) 5 is widely chosen for its comprehensive and robust environmentally-extended input-output methodology.

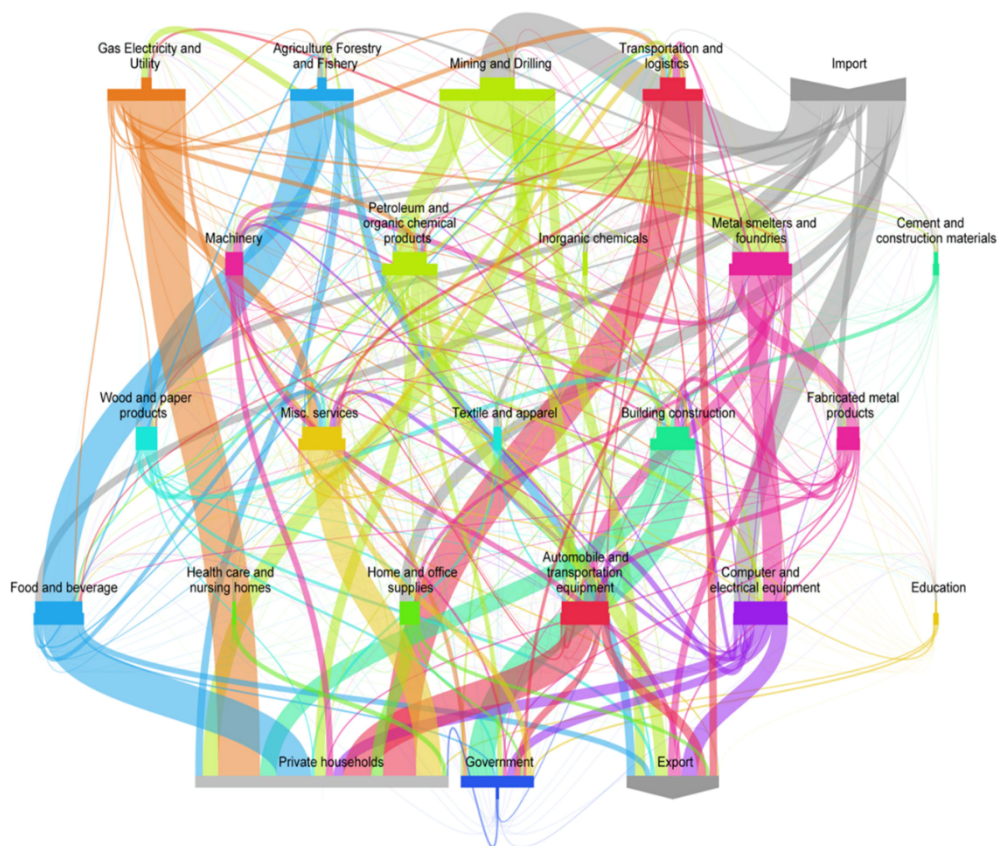


Figure A2 6. Flows of environmental impacts from raw materials to final demand in CEDA. This is an index of all environmental indicators, not just GHG emissions

Financial flows in input-output tables are ultimately allocated to final demand, including households, government activities and investment capital. The tables also include flows of international imports and exports for each sector. CEDA traces all flows of greenhouse gas emissions to households and government activities. Emissions from capital investments, mostly from the life cycle of building construction and equipment, are allocated to sectors and distributed proportionally to household and government consumer products and services from those sectors. Imports are assumed to be

produced with the same carbon intensity as domestically-produced goods and services. Future updates to our current methodology may incorporate the effect of imports using a multi-regional input-output model.

Greenhouse gases include carbon dioxide (CO₂), methane (CH₄), Nitrous Oxide (N₂O) and other high global warming potential gases (HFCs, PFCs, SF₆ and NF₃). CEDA produces emission factors as kg CO₂ equivalent per dollar of sector output in producer or purchaser prices. Producer prices are at factory gate, while purchaser prices include value added from transportation to market, plus wholesale and retail markups, and are the prices paid by final consumers.

A simple approach to estimate emissions from consumer goods and services would be to multiply average household expenditures by CEDA emission factors. This would underestimate emissions considerably, since BEA and BLS accounts do not coincide. Personal Consumption Expenditures, as calculated by BEA, sum up to \$11 trillion in 2012 out of \$16 trillion gross domestic product (GDP). Total household expenditures, as reported by BLS in the CES, were only \$6.4 trillion, or ~40% of GDP, and ~60% of personal consumption expenditures (as reported by BEA). Input-output tables are based on BEA accounts, and thus applying emission factors in CEDA (or any other IO model) would greatly underestimate emissions per consumer dollar in the CES. To solve this problem, we use CEDA emission factors for consumer products up until the factory gate (in producer prices), and then apply value-added emissions from transportation, wholesale and retail trade to create an emission factor at point-of-sale (Jones and Kammen 2011). We then divide by total household expenditures to create emission factors in CES dollars. The final results are shown in the table below.

Table A2 2. Average U.S. Household Consumer Expenditures, GHG Emissions and Carbon Intensity in 2015

	USEXPENDITURES	CO2E	CEXINTENSITY
FOOD	8,053	7.28	905
Alcoholicbeverages	580	0.41	700
Cerealsandbakeryproducts	526	0.60	1,149
Dairyproducts	446	0.60	1,344
Foodawayfromhome	3,199	1.95	610
Fruitsandvegetables	858	0.87	1,011
Meatspoultryfishandeggs	901	1.28	1,423
Otherfoodathome	1,543	1.57	1,019
GOODS	7,102	4.54	640
Apparelandservices	2,119	0.95	448
EntertainmentGoods	1,794	1.74	972
FloorCoverings	127	0.06	489
Furniture	620	0.26	424
HouseholdTextiles	86	0.14	1,680
Housekeepingsupplies	647	0.34	518
MajorAppliances	351	0.14	398
MiscHousholdEquipment	607	0.11	173
Personalcareproducts	300	0.30	987
Reading	136	0.13	957
SmallAppliancesMiscHousewares	77	0.22	2,929
Tobacoproductsandmokingsupplies	238	0.15	629
HOME	16,283	10.23	629
Shelter	11,948	1.32	110
Otherlodging	738	0.35	473
Utilitiesfuelsandpublicservices	3,597	8.57	2,382
SERVICES	18,384	8.81	479
Cashcontributions	1,985	0.36	179
Education	1,237	1.15	926
EntertainmentServices	1,304	1.56	1,193
Healthcare	4,321	4.17	966
Householdoperations	1,430	0.61	424
Miscellaneous	1,023	0.08	75
Personalcareservices	451	0.22	486
Personalinsuranceandpensions	6,633	0.68	103
TRANSPORTATION	9,396	4.46	475
Gasolineotherfuelsandmotoroil	2,415	0.89	371
LocalPublicTransportationExclOnTrips	148	0.21	1,438
Othervehicleexpenses	2,981	1.49	499
PublicAndOtherTransportationOnTrips	625	0.91	1,451
Vehiclepurchases(netoutlay)	3,227	0.96	297
GRAND TOTAL	59,218	35.33	597

Emissions from motor vehicles, totaling 11 tCO₂e in 2015, are not included in the table above.

3. Back-casting US Carbon Footprints to 1990

Section 1 above describes the change in consumption in constant 2015 USD over time. Comparing consumption in constant dollars shows the change in physical units over time, such as pounds of food, number of televisions, or number of services purchased. Section 2 describes the methods for estimating full life cycle GHG emissions for each category of consumption in the year 2015. In order to show change in carbon footprints over time, we need a database of carbon intensity over time. To date, no such database of carbon intensity exists. The CEDA database goes back only as far as 1997, and each version of the database has improved over time, using somewhat different assumptions. Based on discussion with the developer, Dr. Sangwon Suh, we determined that the best way to track changes in carbon intensity over time would be to compare total household consumption in constant 2015 USD with total US emissions. This corresponds to a roughly 1% annual decrease in carbon-intensity over time. We further compared constant expenditures with direct emissions from agriculture. During the same period, normalized carbon-intensity of agriculture remained unchanged.

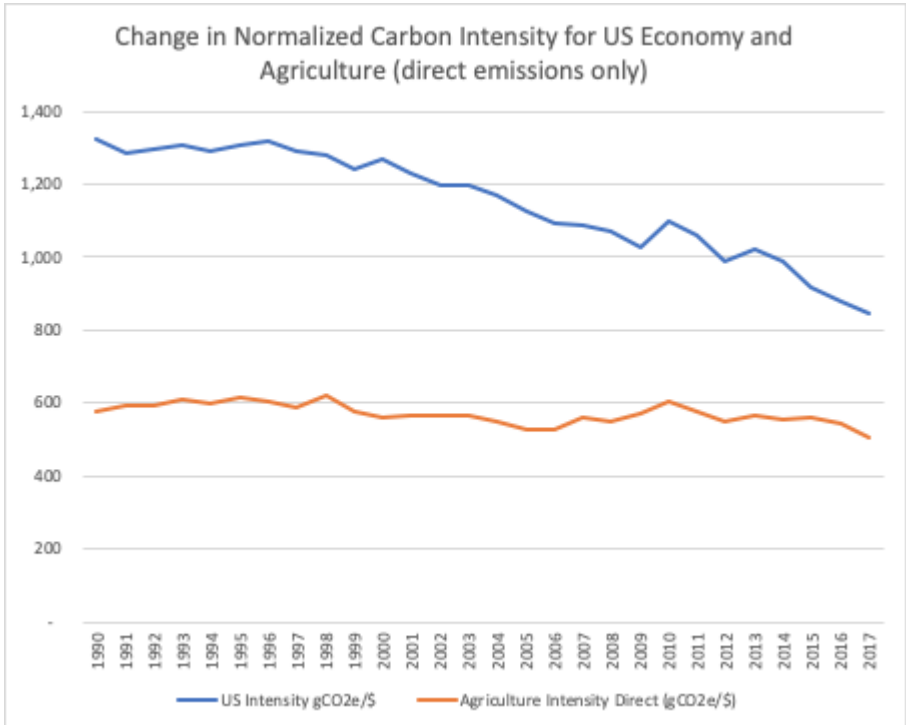


Figure A2 7. Change in normalized carbon intensity for U.S. economy and agriculture (direct emissions only)

Some major sources of emissions from agriculture have increased, including methane emissions enteric fermentation and manure management, while nitrous oxide emissions from soil management have remained roughly constant. The direct emissions include food production for domestic consumption and export. Exports of food have increased dramatically over 25 years, but still account for only about 20% of US agriculture production.

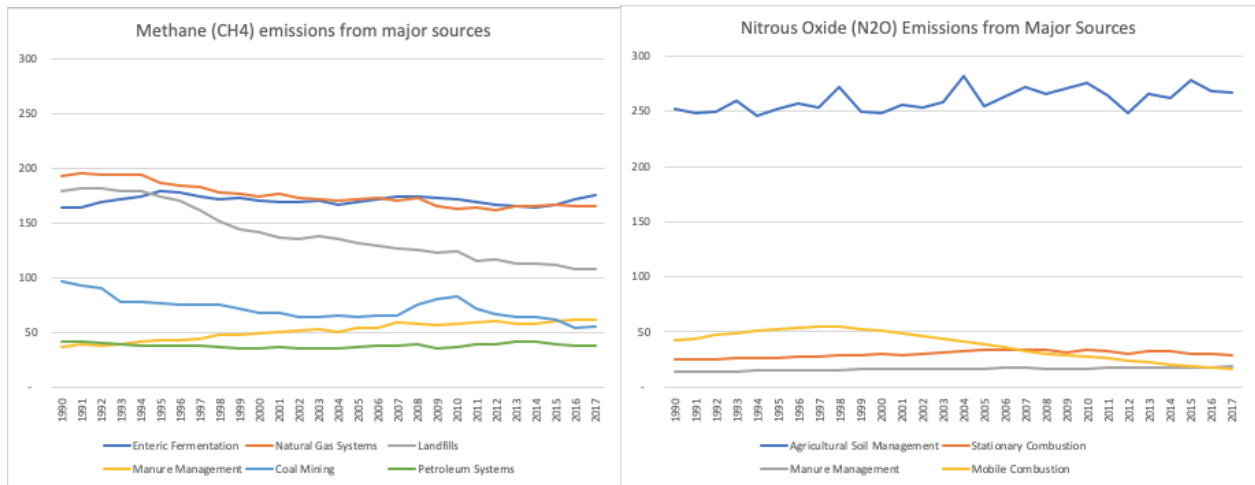


Figure A2 8. U.S. methane (left-hand figure) and nitrous oxide (right-hand figure) emissions from major sources

Based on this evidence we assumed the carbon intensity of US agriculture has decreased by 0.5% per year since 1990, while the carbon intensity of all other categories of consumption decreased by 1% per year in CPI-adjusted 2015 USD.

4. Calculating US Carbon Footprints from 1990 to 2015

Household carbon footprints are calculated as the sum of the products of consumption (in USD) and carbon intensity (gCO₂/USD) for all categories of consumption over a given year.

Combining the methods described in Sections 1 through 3 above, we estimate a first draft of U.S. household carbon footprints from 1990 to 2015. However, a few additional steps are needed to calculate a full consumption-based inventory for the United States. Input-output tables do not include consumption of gasoline from personal motor vehicles so this must be added. Additional steps are also needed to include emissions associated with federal, state and local government activities.

4.1. Motor Vehicles

We calculated emissions from motor vehicles as follows:

$$\text{VMT} / \text{MPG} * (\text{CI-direct} + \text{CI-indirect})$$

Where,

VMT = Vehicle miles traveled from the National Household Travel Survey

MPG = Average on-road fuel economy of light duty vehicles ([Sivak](#))

CI-direct = CO₂ per gallon of gasoline (EPA)

CI-indirect = Indirect CO₂ per gallon of gasoline (GREET Model)

Average on-road fuel economy of light duty vehicles increased from 20 mpg in 1990 to 23 mpg in the United States. Each gallon of gasoline produces about 10 kg of CO₂ when combusted. We multiple by 1.2 to account for well-to-pump emissions using output from the US EPA GREET model.

4.2. Government Emissions

Roughly 20% of all emissions in CEDA are from government activities, including federal, state and local government consumption. Figure A2 10 shows the carbon intensity (kg CO₂e per US) of each major category of government spending. The carbon intensity of defense spending is roughly 2x larger than non-defense spending. Total US government spending was about [\\$8 trillion in 2014](#). We estimate government emissions to be roughly 1 billion metric tons of CO₂e in 2015.

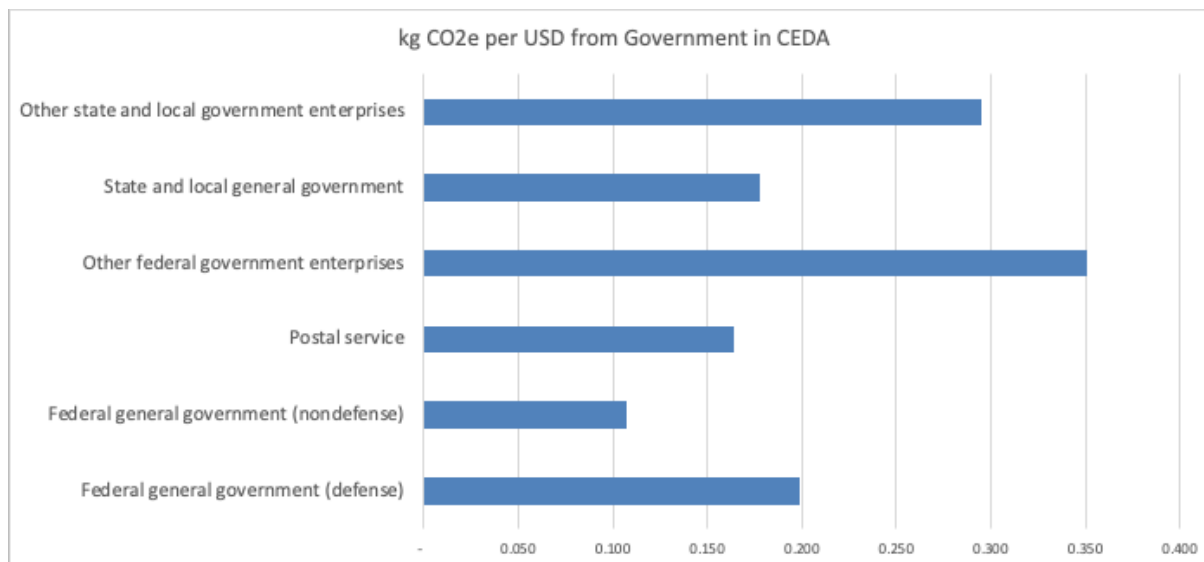


Figure A2 10. Kg CO₂e per USD from Government in CEDA 5

Several methods of allocating government emissions to local governments, including per capita, per household, and per tax revenues. For simplicity, we choose to allocate government emissions as equivalent to 15% of household carbon footprints. This allocates all government emissions based on household contributions to greenhouse gas emissions. Households and governments combined consist of all U.S. final demand in CEDA, and correspondingly in our approach. Since we assume government emissions are simply a factor of household emissions, all U.S. emissions (from businesses, governments and households) are allocated to households in our approach. Future studies could refine this methodology to delineate local, state and federal emissions.

4.3. Total US Consumption-Based GHG Emissions: 1990 - 2015

Figure A2 11 compares the traditional sectoral-based US GHG inventory (US EPA) with the consumption-based GHG inventory. The consumption-based inventory is about 10% larger than the traditional inventory due to the difference between U.S. imports and exports. We assume imports are produced with the same carbon intensity as domestic production. Transportation is the largest categories of emissions in both the sectoral and consumption-based approach. Emissions from residential (heating fuels) in the sectoral approach is combined with residential electricity, home construction, waste, water, and household operations in the consumption-based approach. Emissions from

Industry in the sectoral approach are split into goods, services, transportation, housing and food. Emissions from Commercial in the sectoral approach only includes heating fuels, whereas Services in the consumption-based approach includes the full life cycle of goods and services consumed by the services sectors, as well as direct and indirect emissions from energy and transportation used by that sector.

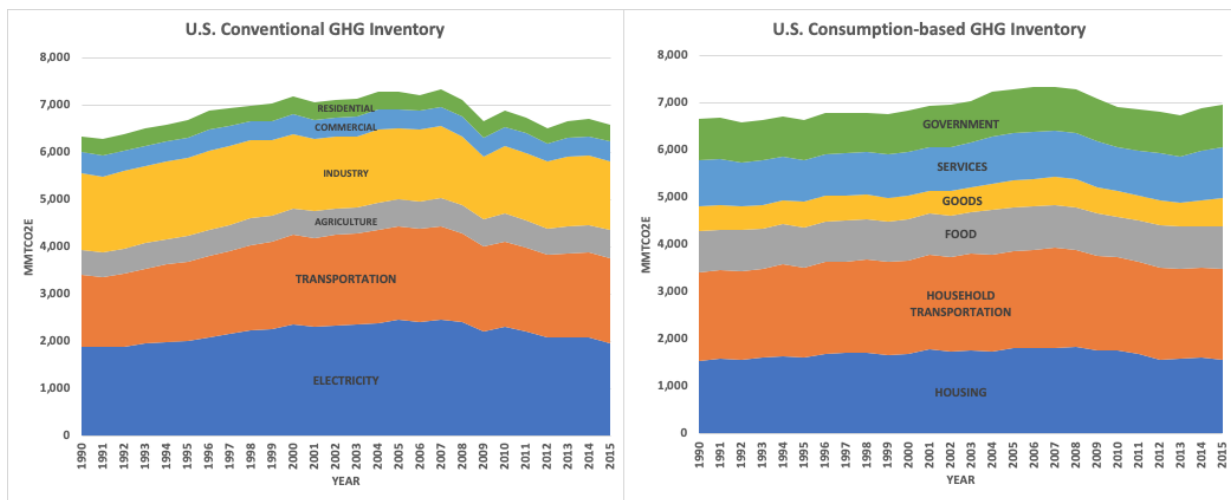


Figure A2 11. U.S. traditional (territorial) versus consumption-based GHG inventory

The full dataset includes detailed breakdown of emissions by product category. Please visit the CoolClimate Calculator for detailed information on household carbon footprints for any U.S. location: <https://coolclimate.org/calculator>.

5. Estimating Consumption and Carbon Footprints for San Francisco County

Consumption-based greenhouse gas inventories rely on accurate assessment of all aspects of household consumption, including transportation, household energy, building construction materials and discards, food, goods and services. The primary purpose of this study is to identify the driving factors of household consumption and use this information to estimate carbon footprints for any location. As discussed previously, we use econometric analysis of national household survey data to develop models for dozens household expenditures. We then apply model results to each location based on local variation in those same variables. By including more variables in our model, we are able to more accurately estimate household consumption than using income alone.

Due to privacy and data reliability concerns, national household surveys rarely provide the geolocation of survey respondents other than Census region or the state of residence. The Consumer Expenditures Survey includes a subsample for metropolitan areas, including the 5-county San Francisco-Oakland-Hayward metropolitan area. After extensive trial and error, we determined that the margin of error using these results was too large to warrant further investigation. Several important product categories, such as “meat, fish and eggs” demonstrated considerable volatility over time that was not reflected in the larger national sample. See Appendix 1 for details. We therefore analyze and develop models of consumption using the entire US sample of microdata in the Consumer Expenditures Survey for the year 2015.

5.1. Econometric Analysis of Variables and Hypothesis

The following independent variables were explored in models to predict consumption:

AGE = the age of the survey respondent in years
DETTACHED = the home is single-family detached
OWN = the home is owned
DEGREE = the survey respondent achieved at least a 4-year college degree
HHSIZE = the number of people in the household
INCOME = the total annual household income before taxes
WHITE = the race of the survey respondent was "white"
ROOMS = the total number of rooms in the home (a proxy for home size)
MALE = the survey respondent is male
WEST = the Census region is WEST
VEHICLES = the number of vehicles per household
MSA = the household lives in a metropolitan statistical area

After considerable experimentation we found six variables (Income, Household size, Home size, Education level, Home Ownership, and Vehicle Ownership) to be the strongest consistent predictors of household consumption. Income (AVGINCOME), household size (HHSIZE) and the size of homes (ROOMS) consistently have the strongest correlation with expenditures. Education level (DEGREE), home ownership (OWN) and vehicle ownership (VEHICLES) are strongly correlated with different categories of expenditures.

Hence, we hypothesize the following:

1. Income will be positively correlated with all categories of consumption.
2. Household size will be strongly correlated with personal expenses, such as food, clothing and education, but less strongly with consumption related to homes.
3. Home size (number of rooms) will be strongly correlated with home furnishings and appliances.
4. College degree will be strongly correlated with consumption related to social status, such as education and air travel.
5. Home ownership will be positively correlated with expenditures on homes, such as appliances and furnishings.
6. Number of vehicles will be strongly correlated with vehicle travel.

The model forms are:

$$\log(\text{Expenditures}_i) = \beta_0 + \beta_1 * \log(\text{INCOME}) + \beta_2 * \log(\text{HHSIZE}) + \beta_3 * \log(\text{ROOMS}) + \beta_4 * \text{OWN} + \beta_5 * \text{DEGREE} + \beta_6 * \text{VEHICLES}$$

Table A2 3. Model output (Betas) for each major consumption category (rows) and independent variable (columns)

index	HHSIZE	INCOME	ROOMS	OWN	DEGREE	VEH
PersonalInsuranceAndPensions	0.110	0.659	0.032	0.049	0.195	0.063
Shelter	0.146	0.256		-0.491	0.350	
TotalExpenditures	0.176	0.248	0.092		0.182	0.082
PublicAndOtherTransportation	0.076	0.242	0.082	0.209	0.146	
VehiclePurchasesNetOutlay	-0.071	0.238	0.117	0.287	0.172	-0.059
Transportation	0.292	0.223			0.092	0.189
EntertainmentServices	0.157	0.214	0.143	0.080	0.264	0.061
CashContributions		0.211	0.311	0.136	0.162	0.048
ApparelAndServices	0.385	0.203	0.085		0.047	0.019
Housing	0.204	0.203	0.008		0.188	0.004
Education	-0.331	0.199	0.126	0.080	0.333	0.082
FoodAwayFromHome	0.107	0.198			0.129	0.028
AlcoholicBeverages	-0.048	0.192			0.110	0.029
Entertainment	0.049	0.185	0.198	0.051	0.157	0.062
LocalPublicTransportation	0.372	0.182				-0.228
OtherLodging		0.179	0.004		0.178	
Furniture		0.172		0.223		
PersonalCareProductsServices	0.143	0.170	0.089		0.090	
HouseholdOperations	0.118	0.167	0.235	0.010	0.167	
Housekeepingsupplies	0.118	0.167	0.235	0.010	0.167	
MiscellaneousExpenditures		0.161	0.081			0.026
HouseholdTextiles		0.157	0.088	0.010		0.001
TransportationOnTrips	0.138	0.152	0.047	0.082	0.103	
HouseFurnishingsEquipment	0.119	0.151	0.102	0.145		0.043
TotalFood	0.358	0.147	0.006		0.068	0.031
MiscHoushouseholdEquipment	0.088	0.136	0.009	0.061		0.056
Healthcare	0.031	0.131	0.208	0.307	0.024	0.062
Gasolineotherfuelsandmotoroil	0.351	0.111				0.129
SmallAppliancesMiscHousewares		0.110	0.055	0.040		0.048
Reading		0.105	0.081		0.011	
Othervehicleexpenses	0.049	0.105				0.076
EntertainmentGoods	0.021	0.103	0.141	0.062		0.034
FloorCoverings		0.091	0.214	0.796		0.009
FoodAtHome	0.465	0.082				0.015
UtilitiesFuelsAndPublicServices	0.248	0.076	0.369	0.235		0.041
TobaccoAndSmokingSupplies	0.031	0.053				0.034
MajorAppliances		0.041	0.317	0.671		

5.2. Testing of Independent Variables

As discussed above Income, Household Size, Home Size, College Degree, and Vehicle Ownership seem to be the top variables influencing consumption. Table A2.1 is a summary of results (betas), sorted by income elasticity. Analysis of the effect of each independent variable on categories of consumption follows.

5.2.1 Income

The main drivers of emissions vary considerably by consumption category. Income is a significant contributing factor to all household consumption, with an average elasticity of 0.25, meaning a 1% increase in income corresponds to 0.25% increase in consumption, with a range of 0.03 to 0.66. However, for important categories such as food consumed at home, income has very little impact on consumption (income elasticity = 0.08; household size elasticity = 0.46). Food, healthcare, education and personal services depend largely on household size. Household goods, such as furniture, appliances and floor coverings, depend more on home ownership and the size of homes. Motor vehicle usage depends on vehicle ownership and household size, while energy depends on home structure, demographics, weather and other factors.

The overall income elasticity of demand for all expenditures is 0.25, meaning a 1% change in income corresponds to 0.25 percent change in expenditures. Income elasticities vary considerably by consumption category, from $\beta = 0.03$ for prescription drugs to 0.66 for personal insurance and pensions. Income has a largest effect on categories of consumption that do not correspond with higher emissions. Pensions and insurance are largely savings, and the effect of this economic activity on total emissions is negligible, relative to other categories of emissions. Expenditures on shelter are large in San Francisco, but this is not a function of larger, more carbon-intensive homes, but rather a market effect. Cash contributions (donations), domestic services and education represent a second tier of emissions related to income; however, the carbon intensity of these services is relatively small and it is not clear that more expenditures on education translates to higher emissions, or that donating to charity should necessarily correspond to higher emissions.

A few categories of carbon-intensive consumption are strongly affected by income. Higher income households are much more likely to fly (income $\beta = 0.24$); home ownership ($\beta = 0.21$) and college degree ($\beta = 0.15$), variables associated with social status, also play a role. Given the high carbon-intensity of air travel, high income, well educated, professional communities are likely to have higher than average impacts from air travel. The proximity of a major international airport in San Francisco may also play a role. Food away from home (eating out) is more strongly affected by income ($\beta = 0.16$) than other variables studied; however, the carbon-intensity of food consumed at restaurants is lower on a per dollar basis than food consumed at home (CEDA database), presumably because prices are higher. Eating at restaurants may also be more efficient in terms of energy because patrons are sharing heating, lighting, cooking and other energy needs. For most other categories of food, goods and services, either household size, home size and home ownership is more strongly correlated with expenditures; however, income is statistically significant and positive for all categories

of consumption, and it adds up to the largest overall contribution to household expenditures.

5.2.2 Household Size

Two-thirds of household expenditures are significantly affected by household size. Food at home, in particular, is largely determined by number of people ($\beta = 0.46$). This follows, since food is the source of all human energy, and people generally consume food multiple times a day. Controlling for household size, income has little effect on expenditures on food at home ($\beta = 0.08$) and this is likely due to purchase of more expensive food, not quantity (Jones and Kammen, 2011). Similarly, clothing, another basic need, is largely a function of household size ($\beta = 0.39$). The effect of income on clothing (elasticity 0.2) may also largely be due to prices (e.g., name brands), rather than quantity of clothing purchased. As anticipated by hypothesis 2, household size is also a significant contributing factor to personal products and services, healthcare, and utilities. Household size is 15% smaller in San Francisco vs. the US (2.2 vs. 2.6 persons per household) so expenditures on food, clothing and personal items per household should be lower than U.S. overall.

5.2.3 Home size

As predicted in hypothesis 3, the size of homes is strongly correlated with expenditures on major appliances ($\beta = 0.32$) and home furnishings ($\beta = 0.1$), as well as utilities ($\beta = 0.37$), domestic services ($\beta = 0.8$), and household operations ($\beta = 0.23$). Fully three quarters of expenditures are positively correlated with home size. There is perhaps a surprisingly strong correlation between homes size and expenditures on personal consumption categories, such as healthcare ($\beta = 0.2$), and education ($\beta = 0.13$). It may be that the size of homes is correlated with consumptive lifestyle generally, or that multicollinearity between independent variables causes home size to capture some of the residual effect of other variables. In any case, consideration of the size of homes appears to be critically important for accurately estimating household consumption. Home sizes 22% smaller than the national average so expenditures on household items can be expected to be lower.

5.2.4 Home ownership

Over 50% of household expenditures are influenced by home ownership. It is logical that renters are less likely to invest properties they do not own or to purchase expensive furniture or other household items. Home ownership is most significant for floor coverings ($\beta = 0.8$) major appliances ($\beta = 0.65$) and other household furnishings and equipment. Homeowners naturally also spend more on utilities, which follows since renters do not always pay all utility bills. Home ownership also appears to be associated with quality of life improvements, and consumption associated with social status, such as air travel, education, and cash contributions. Only 39% of San Francisco households own their home, compared to 65% nationally. As a result, expenditure related to home ownership can be expected to be considerably lower than the national average.

5.2.5 College degree

Attainment of a college degree is strongly correlated with over 50% of household expenditures, even when controlling for income, household size, home size and home ownership. Higher educated households simply spend more, particularly on expenditures related to social status, such as shelter ($\beta = 0.35$) education ($\beta = 0.32$), fees and admissions to entertainment ($\beta = 0.32$), domestic services ($\beta = 0.20$), cash contributions ($\beta = 0.16$) and air travel ($\beta = 0.15$). Over 60% of San Francisco householders have a college degree, which is nearly double the national average. The high level of college education should lead to increased expenditures compared to the metropolitan area and national average.

5.2.6 Vehicle ownership

Motor vehicle ownership is strongly correlated with motor vehicle usage and purchases. Due to relatively low vehicle ownership in San Francisco (1.1 vs. 1.8 nationally), emissions from vehicles should be considerably lower than national averages.

5.3. Adjusting consumption for San Francisco

Our models produce estimates of expenditures that are consistently lower than national averages, particularly for infrequent purchases. This is because some purchases are infrequent and BLS only tracks households for a few months of the year. Some large purchases, such as flooring, furniture, motor vehicles or large appliances are made very infrequently. As a result, expenditures in the micro data are zero for many expenditure categories for most households. BLS uses a complex weighting system to annualize expenditures for these categories to produce an accurate annual average. Since we are interested in the percentage change in consumption based on modeled household characteristics (income, household size, home size, education, home ownership and vehicle ownership) we calculate total expenditures as follows:

$$\text{Actual}_{\text{US}} * \text{Predicted}_{\text{location}} / \text{Predicted}_{\text{US}}$$

Where,

- $\text{Actual}_{\text{US}}$ = US average expenditures per household as tabulated by BLS in summary tables
- $\text{Predicted}_{\text{location}}$ = Our modeled estimate of expenditures for each location, in this case San Francisco
- $\text{Predicted}_{\text{US}}$ = Our modeled estimate of expenditures for the United States

This approach modifies national consumption by a scaling factor ($\text{Predicted}_{\text{location}} / \text{Predicted}_{\text{US}}$) based on differences between modeled variables in each location and the national average. For example, if actual average U.S. consumption of a category of consumption is \$2,000 per year, but our model only predicts \$1,500 for households with average U.S. characteristics and \$1,250 in San Francisco, our estimate for San Francisco would be $\$2,000 \times \$1,250 / 1,500 = \$1,666$, or 83% of the national average.

5.4. Carbon Intensity of Food, Goods and Services in San Francisco

We assume the carbon intensity of food, goods and services consumed by San Francisco households is the same as the U.S. Average. It may be that locally-produced goods and services have lower carbon-intensity than national averages. We know that local electricity is less carbon-intensive than the national overall. Yet, electricity (known as Scope 2 emissions) tends to be a relatively small part of the carbon footprint of most goods and services when full supply chains are considered. Future versions of this study may attempt to modify the carbon intensity of local food, goods and services by delineating direct and indirect emissions for each product category and modifying the carbon-intensity of electricity.

In the subsequent sections we describe our methods for modifying carbon footprint estimates for local motor vehicles, public transportation, energy consumption and waste.

6. Refining estimates for Transportation

The National Household Travel Survey (NHTS) is a nationally representative household survey of motor vehicle usage in the United States, conducted every 8 years. NHTS includes sub samples for all 50 U.S. states as well as dozens of metropolitan regions, including the San Francisco Bay Area.

Our purpose is to construct multi-variate linear regression models to predict vehicle miles traveled (VMT) using household and community characteristics known at fine spatial resolution for San Francisco, California. For example, we know average household income, average number of vehicles owned, household size, and population density for all U.S. geographies and these data are also recorded for each NHTS survey respondent. Thus, we can create econometric models using NHTS survey data to predict VMT for any and all U.S. geographies based on local information. We tested different models for the city and county of San Francisco, California. Eventually, we will apply a similar model to all U.S. block groups, tracts, zip codes, cities, counties and states in the United States.

6.1 Collecting NHTS data

We use the 1990 NHTS to represent 1990; the 2001 NHTS to represent 2000; the 2009 NHTS to represent 2010 and the 2017 NHTS to represent 2015.

First, we downloaded and imported the 1990, 1995, 2001, 2009 and 2017 NHTS data sets. We need the vehicles (veh), households (hh) and persons (per) data sets. Source: U.S. Department of Transportation, Federal Highway Administration, 2009 National Household Travel Survey. URL: <https://nhts.ornl.gov>. The 2001, 2009 and 2017 surveys are very similar, with most changes related to the methods used to collect data (not definitions of the data), while the 1990 survey was somewhat different and called the National Personal Transportation Survey.

The following table shows the sample size for the SF Bay Area metropolitan statistical region in each survey:

Table A2 4. Sample sizes of NHTS surveys in 1990, 2001, 2009 and 2017

	1990	2001	2009	2017
Variable	CMSA	HHC_MSA	HH_CBSA	HH_CBSA
Core Cities	San Francisco–Oakland–San Jose	San Francisco–Oakland–San Jose	San Francisco–Oakland–Fremont	San Francisco–Oakland–Hayward
FIPS	7362	7362	41860	41860
Sample N	432	601	2,293	2309

The 2009 and 2017 surveys have large enough sample sizes to support multivariate regression models with all variables of interest, but models developed with the 1990 and 2001 surveys may need to have fewer independent variables. We ran step-wise

regression to choose the best models in those years. It is important to use the same independent variables for all model years in order to prevent irregular results.

6.2. Run Multi-variate Regression Models to Predict VMT in San Francisco

Our dependent variable was total vehicle miles per household. We included over a dozen variables: vehicle count, income, household size, population density, commute times, age of householder, race of householder, home ownership, commute mode to work, region and several other potential variables.

After much experimentation with the 2017 NHTS microdata, we found the goodness of fit with just 4 variables is roughly the same as with 10 variables (Adj R2 ~ 0.4 for both). The four-variable model is parsimonious with relatively few policy-relevant variables. Adding more variables to the model (e.g, home ownership or % who drive to work) does not greatly improve the model fit. Parsimony is also important since we ideally want to use the same model form for all years of the NHTS.

Below is a scatterplot matrix of Betas (β) for the four-variable model. As shown in the last column, BESTMILE (our dependent variable of vehicle miles traveled) is most strongly dependent on vehicle count ($\beta = 0.5$), Household Size ($\beta = 0.36$), Household Income ($\beta = 0.26$), with a small weak correlation for Population Density ($\beta = -0.10$). Income, household size and vehicles also show strong multi-collinearity. For the purposes of prediction, collinearity is not a concern, but we should be careful not to draw inferences on the relative impacts of independent variables in regression results.

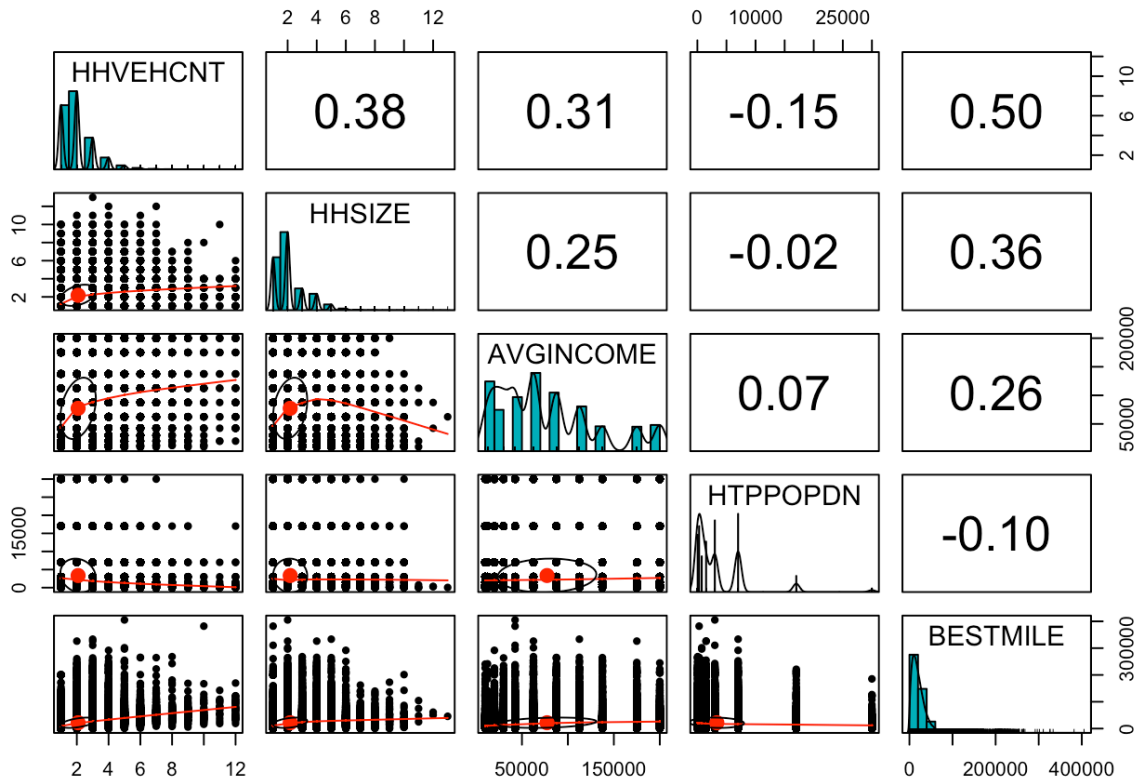


Figure A2 12. Scatter plot matrix of four independent variables (HHVEHCNT – vehicles per households, HHSIZE – persons per household, AVGINCOME – average annual household income, HTPPOPDN – population density) on the dependent variable BESTMILE – annual vehicle miles traveled of all household vehicles

6.3 Model Results

6.3.1. 2017 NHTS

Formula:

$$\ln(\log(\text{BESTMILE17})) \sim \text{HHVEHCNT17} + \log(\text{HHSIZE17}) + \text{AVGINCOME17} + \text{HTPPOPDN17}$$

Table A2 5. Betas with Census Data for City of San Francisco in 2015

	Beta	2015 CENSUS
Intercept	8.467	
$\log(\text{HHVEHCNT})$	0.321	1.1
$\log(\text{HHSIZE})$	0.469	2.35

AVGINCOME	0.0000013	119406
HTPPOPDN	(0.0000055)	18679

VMT for San Francisco = EXP(8.467e+00 + 3.209e-01 * log(1.1) + 4.694e-01 * log(2.35) + 1.320e-06 + 119406 + -5.534e-06 * 18679) = 7,730 miles per household. This is only 36% of the national average of 21,737 miles per household. The average vehicle miles traveled for the U.S. in the 2017 NHTS was 21,737 and 18,322 for the 5-county San Francisco Bay Area.

6.3.2. 2009 NHTS

Call:

lm(log(BESTMILE09) ~ HHVEHCNT09 + log(HHSIZE09) + AVGINCOME09 + HTPPOPDN09)

Residuals:

Min	1Q	Median	3Q	Max
-5.4471	-0.3259	0.0779	0.4619	3.1405

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	8.3504583100	0.0518616987	161.014	< 0.0000000000000002 ***
HHVEHCNT09	0.3260636796	0.0190666066	17.101	< 0.0000000000000002 ***
log(HHSIZE09)	0.4933768336	0.0393399627	12.541	< 0.0000000000000002 ***
AVGINCOME09	0.0000027613	0.0000003574	7.726	0.0000000000000175 ***
HTPPOPDN09	-0.0000070814	0.0000022360	-3.167	0.00156 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7558 on 1976 degrees of freedom

Multiple R-squared: 0.3762, Adjusted R-squared: 0.3749

F-statistic: 297.9 on 4 and 1976 DF, p-value: < 0.00000000000000022

Table A2 6. Betas with Census Data for San Francisco in 2010

	Beta	2010 CENSUS
Intercept	8.350	
log(HHVEHCNT)	0.326	1.15
log(HHSIZE)	0.493	2.26
AVGINCOME	0.0000028	102267
HTPPOPDN	(0.0000071)	18679

Vehicle miles traveled in San Francisco = $\exp(8.350e+00 + 3.261e-01 * 1.15 + 4.934e-01 * \log(2.26) + 2.761e-06 + 102267 - 7.081e-06 * 18679) = 7,692$ miles per household.

The average vehicle miles traveled for the U.S. in the 2017 NHTS was 23,348 and 20,577 in the San Francisco Bay Area.

6.3.3. 2001 NHTS

Table A2 7. Betas with Census Data for San Francisco in 2001

	Beta	2000 CENSUS
Intercept	8.408	
HHVEHCNT	0.346	1.11
log(HHSIZE)	0.480	2.3
AVGINCOME	0.0000028	80325
HTPPOPDN01	(0.0000018)	16634

Vehicle miles traveled in San Francisco = $\exp(8.408e+00 + 3.461e-01 * 1.11 + 4.795e-01 * \log(2.3) + 2.813e-06 * 80325 - 1.843e-06 * 16634) = 8,424$ miles per household.

The average vehicle miles traveled for the U.S. in the 2017 NHTS was 24,795 and 23,504 for the San Francisco Bay Area.

6.3.4. Analysis of 1990 and 1995 NPTS data

The 1990 and 1995 surveys are incompatible with the later surveys. In earlier years the survey relied on self-reported VMT, which vastly underestimated the actual value. Starting in 2001, BESTMILE was calculated using data triangulation, with odometer readings, self-reports and GPS used to calculate annual VMT. In order to estimate VMT in 1990 we scale our results from the 2001 analysis to 1990 by the change in vehicles per household, which is the strong predictive variable. Model results for the 1990 and 1995 NPTS are available upon request from the author.

6.4. Average Annual VMT for San Francisco, SF Bay Area and US

The results for the City of San Francisco, compared to the U.S. and SF Bay Area are shown below.

Table A2 8. Vehicle Miles Traveled in SF Bay Area vs. San Francisco

USA	SF Bay Area	San Francisco
-----	-------------	---------------

1990	24,570	23,540	8,045
1991	24,592	23,537	8,082
1992	24,615	23,533	8,120
1993	24,637	23,529	8,158
1994	24,660	23,526	8,196
1995	24,682	23,522	8,234
1996	24,705	23,519	8,272
1997	24,727	23,515	8,310
1998	24,750	23,511	8,348
1999	24,772	23,508	8,386
2000	24,795	23,504	8,424
2001	24,650	23,211	8,378
2002	24,505	22,919	8,332
2003	24,361	22,626	8,285
2004	24,216	22,333	8,239
2005	24,071	22,041	8,193
2006	23,926	21,748	8,147
2007	23,781	21,455	8,101
2008	23,637	21,162	8,054
2009	23,492	20,870	8,008
2010	23,347	20,577	7,962
2011	23,025	20,126	7,916
2012	22,703	19,675	7,869
2013	22,380	19,223	7,823
2014	22,058	18,772	7,776
2015	21,736	18,321	7,730

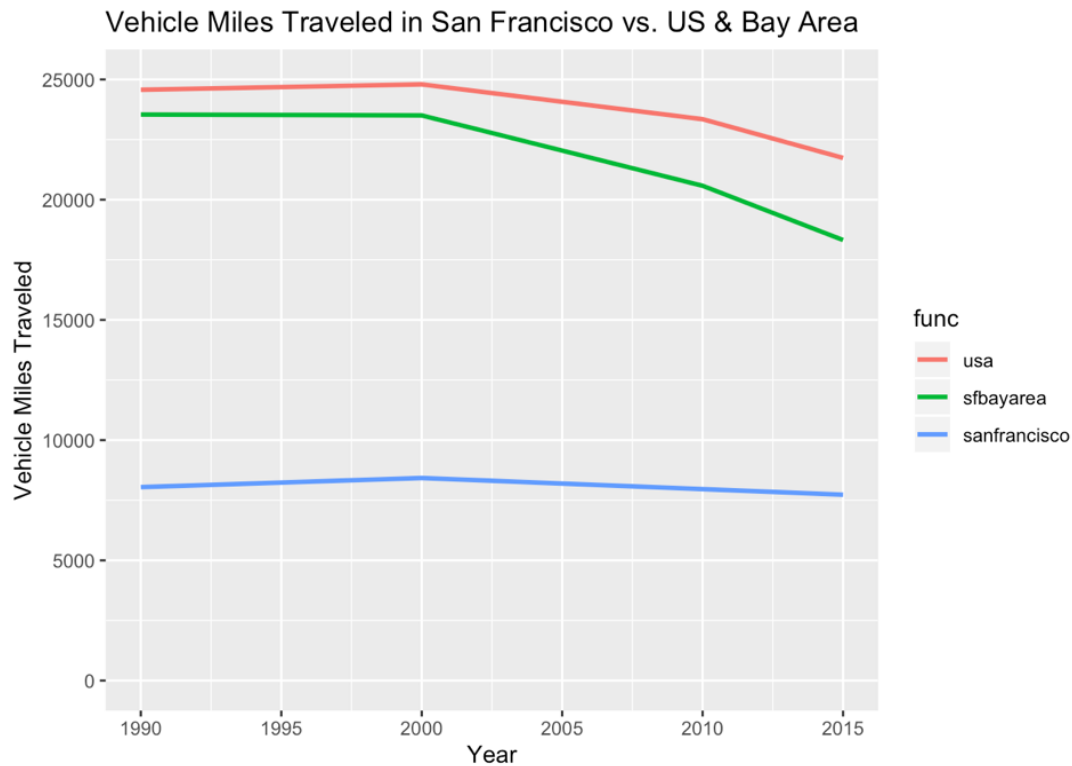


Figure A2 12. Vehicle Miles Traveled in San Francisco, SF Bay Area and US

VMT in San Francisco is less than 50% of average Bay Area VMT. VMT rose slightly in 2000, and has decreased slowly over the past 15 years, for a net of 4% reduction since 1990, compared to 12% reduction for the US and 22% for the San Francisco Bay Area.

Our results are comparable to California Air Resources Board (CARB) estimates for San Francisco using the EMFAC model (EMFAC). CARB estimates VMT for San Francisco County at 12,839 in 2000 and 13,153 in 2015. CARB considers all vehicles that travel within San Francisco. Our estimate, on the other hand, includes only vehicle miles driven by San Francisco residents, regardless of where they drive.

Low vehicle ownership largely explains the difference. San Francisco households own, on average, only 1 vehicle compared to nearly 2 vehicles per household nationally. Household size and population density also play a role. In addition to owning fewer vehicles, it is reasonable to expect that vehicles travel shorter distances per vehicle. For example, San Franciscans commute far less than most U.S. households by car. Seventy-five percent of San Francisco’s working population in 2015 worked within the city and only 44% drove or carpooled to work (47% including taxis and motorcycles). The rest took public transit, walked, biked or worked from home. Commute mode is a strong indication of mode choice for other mobility purposes, including entertainment, shopping and travel.

7. Air Travel

The following is reprinted from Jones (2015)

Economic expenditures on air travel for each location are approximated using the Consumer Expenditures Survey (CEX) (Bureau of Labor Statistics 2013) with the household income as the independent variable. Household income is the largest factor contributing to air travel in the United States, with other variables, such as population density, trip distance and the presence of low-cost airlines having mixed and often complex relationships (Bhadra 2003). Figure A2. 3 presents data from the 2005 Consumer Expenditures Survey (Bureau of Labor Statistics 2006) and demonstrates that income is highly correlated with expenditures on air travel, but not other modes of public transportation. To obtain S.F. Bay Area estimates of air travel expenditures we use multiple average S.F. Bay Area expenditures on Public Transit in the 2013 CEX (\$1,116) by the fraction of public transit expenditures spent on air travel in each income bracket in 2005. These values were then multiplied by the average cost of air travel in 2013, 5.83 miles per \$, (Bureau of Transportation Statistics 2013) to obtain average miles of air travel for each income bracket.

A typical flight produces direct emissions of 223 grams of CO₂ per passenger mile (Ranganathan et al. 2004), plus a roughly equivalent amount of atmospheric warming due to high altitude water vapor and effects on high altitude atmospheric chemistry (Sausen et al. 2005). While there is considerable amount of variation in both direct and indirect emission for individual flights, these differences should be moderated when considering average values for multiple flights by multiple households in each location.

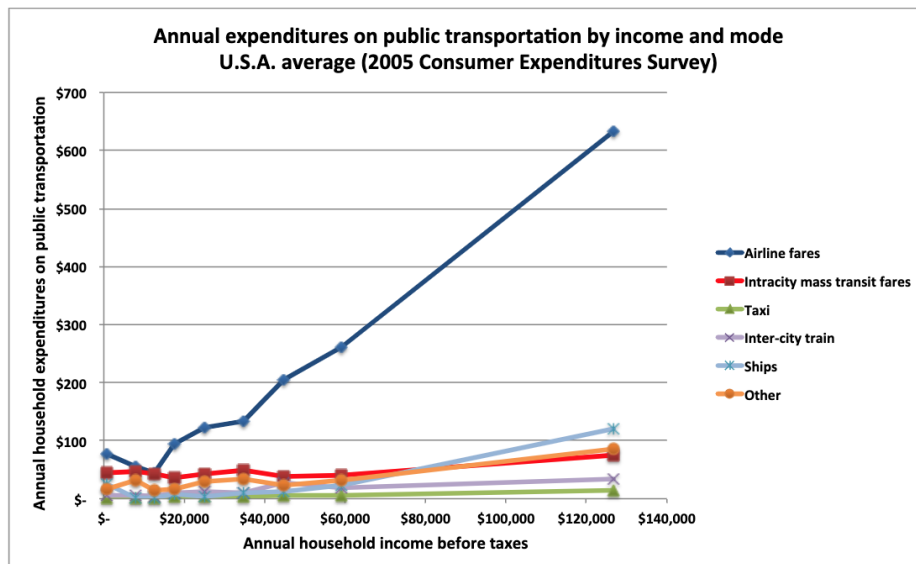


Figure A2 13. Public transportation expenditures by household income. Each mark is the mean value for each income bracket

8. Public Transportation

See Jones (2015) for estimate of public transportation in San Francisco.

Greenhouse gas emissions from S.F. Bay Area public transit systems are roughly approximated using the National Transit Database. Here we include only direct and indirect emissions from fuels; emissions from the life cycle of equipment and public infrastructure are assumed to be included in government emissions. S.F. Bay Area

public transit systems reporting fuel consumption are reported in Table A2 2. Some public transit vehicles appear to be missing from in database, e.g., buses operated by S.F. Municipal Transit Agency. Electricity is assumed to be procured from PG&E. Direct diesel and gasoline emission factors are from EPA (Office of Air Quality Planning and Standards 2013). Indirect GHG emission from gasoline and diesel are from the GREET model (Wang 2008). GHG emission from other fuels are assumed to be 50% of diesel, considered on a life cycle basis. As shown in Table A2 9, total GHG emissions are 149,524 for all public transit systems. We allocated emissions to households in counties served by each public transit system.

Agency	Fare Revenues	kWh electricity	Gallons of Fuel	Metric tons CO2	gCO2 per \$
San Francisco Bay Area Rapid Transit District	\$ 406,889,588	294,344,664	-	52,393	129
San Francisco Municipal Railway	\$ 220,093,193	3,835,961	-	683	3
Peninsula Corridor Joint Powers Board dba: Caltrain	\$ 64,216,475	-	4,394,988	54,885	855
Alameda-Contra Costa Transit District	\$ 61,499,891	-	844,123	6,172	100
Golden Gate Bridge, Highway and Transportation District	\$ 32,129,337	-	164,323	919	29
San Mateo County Transit District	\$ 19,427,746	-	271,913	2,516	129
San Francisco Bay Area Water Emergency Transportation Authority	\$ 10,501,989	-	2,026,809	25,311	2,410
Solano County Transit	\$ 3,945,585	-	236,740	2,956	749
The Eastern Contra Costa Transit Authority	\$ 3,439,725	-	139,678	781	227
Sonoma County Transit	\$ 2,193,485	-	68,011	380	173
City of Santa Rosa	\$ 2,158,609	-	41,739	302	140
Western Contra Costa Transit Authority	\$ 2,034,280	-	78,967	986	485
Napa County Transportation Planning Agency	\$ 926,661	-	54,462	612	661
City of Petaluma	\$ 240,671	-	13,345	75	310
TOTAL SF Bay Area		298,180,625	8,335,098	148,972	

Table A2 9. Revenues, fuel consumption and GHG emissions of SF Bay Area public transit systems Fuel consumption and revenues are from the National Transit Database.

The following is how emissions from public transit systems were allocated to locations:

- San Francisco Bay Area Rapid Transit District - SF, SM, Alameda, Contra Costa counties
- San Francisco Municipal Railway – SF
- Peninsula Corridor Joint Powers Board dba: Caltrain – SF, SM, SCL counties
- Alameda-Contra Costa Transit District – Cities of Alameda, Albany, Berkeley, El Cerrito, El Sobrante, Emeryville, Fremont, Hayward, Kensington, Newark, Oakland, Piedmont, Richmond, San Leandro, San Pablo, and Unity City. Also unincorporated areas including San Lorenzo, Ashland, Cherryland, Castro Valley, Fairview.
- Golden Gate Bridge, Highway and Transportation District – Marin & Sonoma
- San Mateo County Transit District – San Mateo County
- San Francisco Bay Area Water Emergency Transportation Authority – Alameda & Solano counties
- Solano County Transit - Solano
- Victor Valley Transit Authority delete this one, it's in Southern Cal
- The Eastern Contra Costa Transit Authority - cities of Antioch, Pittsburg, Brentwood, Oakley, Bay Point, Discovery Bay and Concord
- Sonoma County Transit – Sonoma
- City of Santa Rosa – City Santa Rosa
- Western Contra Costa Transit Authority - WCCTA service area comprises just over 20 square miles of West Contra Costa County, including the cities of Pinole

and Hercules and the unincorporated areas of Montalvin Manor, Bayview, Tara Hills, Rodeo, Crockett, and Port Costa.

- Napa County Transportation Planning Agency – Napa County
- City of Petaluma –City of Petaluma

9. Electricity and Natural Gas

9.1. San Francisco Energy and Natural Gas Consumption

We obtained electricity and natural gas usage by county from the California Energy Consumption Database (California Energy Commission). Data are shown in figures A2 15 and A2 16. Residential electricity consumption increased slowly from 1990 to 2017, roughly in line with changes in population. Natural gas consumption has declined since 1990.

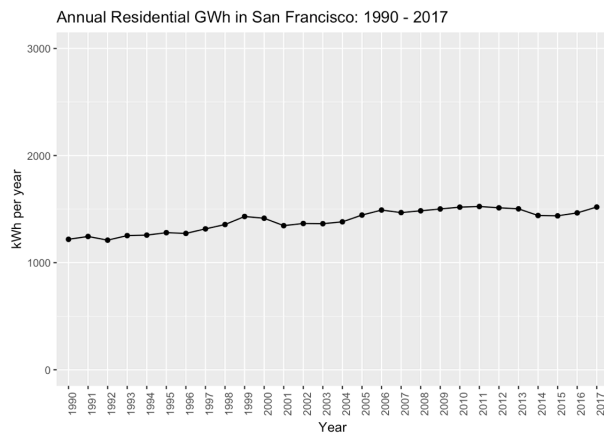


Figure A2 15. Annual residential GWh in San Francisco: 1990 - 2017

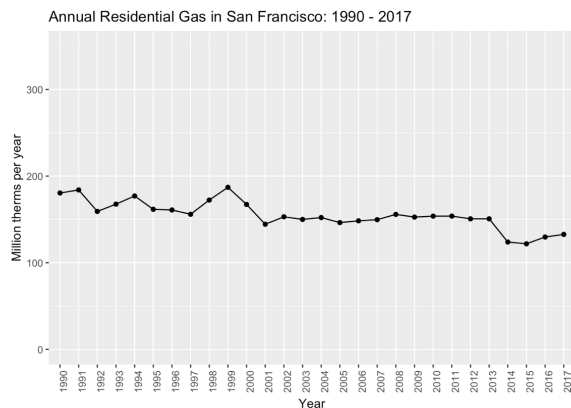


Figure A2 16. Annual residential natural gas in San Francisco: 1990 - 2017

The carbon intensity of electricity is from SF Environment's Greenhouse Gas Inventory. The results from CEC match closing with SF Environment's estimates (Figure A2 17).

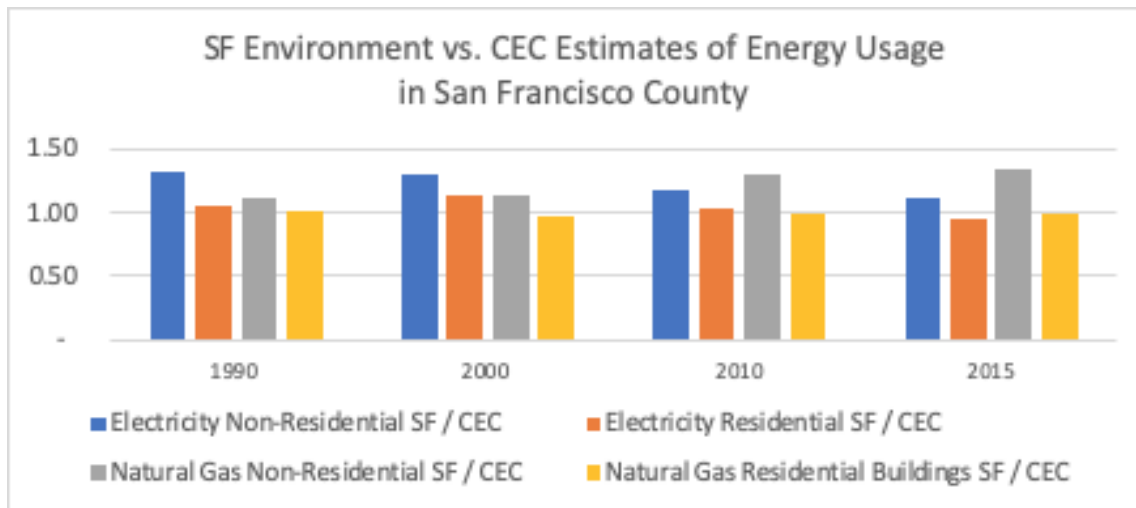


Figure A2 17. SF Environment versus CEC estimates of energy usage in San Francisco County

9.2. Other fuels

We assume a flat 10 gallons of other fuel per year for all SF households. This includes fuel for camping stoves, barbeques, outdoor equipment and other uses.

9.3. Electricity and Natural Gas by Census Tract

The following is reprinted from Jones (2015)

In order to provide higher geospatial resolution to the level of census tract we developed econometric models for electricity and natural gas based on average home characteristics. The modeled results provided a scaling factor for each census block group such that the weighted mean consumption of all households in zip codes matched the mean consumption provided by utilities. In cases where zip codes are served by more than one utility, we create customer-weighted average. Modeled results are used to predict expected consumption based on characteristics of homes in each census block group, provided by the U.S. Census. Two additional data sources were only available at the level of US zip codes: square feet of homes (provided by agreement with CoreLogic) and heating and cooling degree days (interpolated from NOAA weather stations) (NOAA 2015). The US Census provides a concordance table that matches Census Tracts to zip code tabulation areas (ZCTA). For tracts that intersect more than one ZCTA the tract segment with the highest population was mapped to the corresponding ZCTA such that each census tract corresponds to only one zip code. The following section describes methods for modeled results.

Modeled electricity consumption (natural log of kWh per household) is approximated using San Francisco Bay Area respondents in the Residential Energy Saturation Survey (California Energy Commission 2015) ($r^2=0.440$; $n=3,520$; mean =5,909 kWh per year). The variables, entered stepwise and presented in order below, are cooling degree days (CCD) ($\beta=.254$), natural log of income ($\beta=.125$), square feet ($\beta=.294$), CCD * square

feet ($\beta = -.195$), natural log of CCD * square feet ($\beta = .061$), persons per household ($\beta = -.158$), natural log of persons per household ($\beta = .379$), % single-detached homes ($\beta = .074$), % homes owned ($\beta = .099$), number of rooms ($\beta = .158$), % with graduate degrees ($\beta = -.078$), % heat with natural gas ($\beta = .128$), % Asian, ($\beta = -.084$), % black / African American ($\beta = .049$), % White / Caucasian ($\beta = .059$). The purpose of our model is to have the strongest predictive power, not to explain the contribution of different factors to electricity demand. Due to multicollinearity between variables it is not possible to directly interpret the relative impact of individual independent variables on the dependent variable considering the standardized coefficient (β) alone.

Natural gas consumption is modeled from S.F. Bay Area respondents in the Residential Appliance Saturation Survey 2009 ($r^2 = .503$; $n = 3,540$, mean = 411 therms/year) and the following variables (entered stepwise and presented in order): percentage of homes that heat with gas ($\beta = 0.551$), number of rooms ($\beta = -.183$), age of homes ($\beta = .084$), % Asian householders ($\beta = -0.096$), natural log of persons per household ($\beta = 0.058$), % Latino households ($\beta = -0.054$), % of householders with graduate degrees ($\beta = -0.050$), square feet of living area ($\beta = 0.062$), % home owners ($\beta = -0.056$), % single detached homes ($\beta = .052$). Natural gas produces 5,470 gCO₂ per therm (EPA).

10. Water and Waste

For the United States CBEI, we have estimated life cycle emissions from waste, wastewater and municipal solid waste (MSW) by multiplying annual household expenditures by the emission factor for “water and waste” in CEDA 5. This includes full life cycle emissions from material decomposition, wastewater treatment, energy, transportation and full product supply chains. Using this approach, average household emissions from water, wastewater and MSW were 1.62 tCO_{2e} in 1990 and 0.79 tCO_{2e} in 2015

For San Francisco, we used greenhouse data from the 2015 San Francisco GHG inventory for landfilled organics and wastewater. We assume 50% of emissions are from households and therefore divide total emissions by 2 and then by the number of households in San Francisco for each year available (1990, 2000, 2005, 2010, 2012 and 2015), interpolating to fill in missing years.

11. Home Construction

Emissions from home construction are from CEDA 5. CEDA considers all life cycle emissions from materials and energy used during the construction of residential buildings, plus full supply chain emissions from goods and service purchased by the construction sector. We assume emissions scale linearly with the size of homes. The average US home has 5.8 rooms compared to 4.3 in San Francisco in 2015, therefore we assume emissions embodied in buildings are $4.3/5.8$ or 74% of the national average of 2.1 tCO_{2e} in 2015, or 1.55 tCO_{2e} per year.

Appendix 3. Consumer Expenditures Survey: 1990 – 2017

Item	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	015/199	
Number of consumer units (in thousands)	96968	97918	100019	100049	102210	103123	104212	105576	107182	108465	109387	110339	112108	115356	116282	117356	118843	120171	120770	120847	121107	122287	124416	125670	127006	128437	129549	130001	1.32	
Income before taxes	31899	33901	33854	34868	36181	36918	38014	39926	41622	43951	44649	47930	51128	54453	58712	60533	63091	63563	62857	62481	63685	64877	66877	69627	74664	73573	74664	73573	2.18	
Person	2.6	2.6	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	
Average annual expenditures	28381	29614	29846	30692	31731	32264	33797	34819	35535	36995	38045	39518	40677	40817	43395	46409	48400	49638	50486	49067	48109	49705	51442	51100	53495	55978	57311	60060	1.97	
Food	4296	4271	4273	4399	4411	4505	4698	4891	4910	5031	5158	5321	5375	5340	5781	5931	6111	6133	6443	6372	6129	6458	6599	6802	6759	7023	7203	729	1.63	
Food at home	2485	2651	2643	2735	2712	2803	2876	2880	2780	2915	3021	3086	3099	3129	3417	3297	3417	3465	3744	3753	3624	3838	3921	3977	3971	4015	4049	4363	1.62	
Cereals and bakery products	368	404	411	434	429	441	447	453	425	448	452	450	442	461	445	446	446	507	506	502	511	538	544	519	518	524	564	1.41		
Cereals and cereal products	129	145	141	160	162	165	166	161	146	160	156	156	154	150	154	143	143	143	170	173	165	175	182	185	176	172	172	176	1.33	
Bakery products	240	259	270	274	267	276	281	292	278	288	297	296	296	292	307	302	304	317	337	334	337	356	356	359	343	346	353	388	1.44	
Meats, poultry, fish, and eggs	668	709	687	734	732	752	737	743	723	749	795	828	798	825	880	764	797	777	846	841	784	832	852	856	892	896	890	944	1.34	
Beef	218	228	210	234	227	228	215	224	218	220	238	248	231	246	265	228	236	216	239	226	217	223	226	219	232	245	244	253	1.12	
Pork	132	144	156	154	156	157	157	146	157	167	177	167	171	181	153	157	150	163	168	144	162	166	170	177	165	169	181	1.25		
Other meats	99	102	94	98	94	104	99	96	92	97	101	102	101	102	108	103	105	104	106	114	117	123	122	119	123	124	120	128	1.25	
Poultry	108	122	123	137	144	144	145	137	136	145	144	144	145	156	134	141	138	144	154	154	159	170	172	172	172	172	172	186	1.59	
Fish and seafood	82	81	77	87	89	87	89	89	88	89	98	110	114	124	128	133	122	122	128	135	117	121	126	122	129	126	130	140	1.54	
Eggs	30	31	28	30	30	30	34	33	32	32	34	35	34	32	42	33	37	43	51	44	46	50	53	56	58	63	56	55	2.10	
Dairy products	295	294	302	295	289	297	312	314	301	322	325	332	328	328	371	378	368	387	430	406	380	407	419	414	423	413	410	450	1.40	
Fresh milk and cream	140	129	134	128	127	123	132	128	120	122	131	136	127	127	144	146	140	154	168	144	141	150	152	152	147	140	139	147	1.00	
Other dairy products	155	165	168	167	162	174	180	186	181	200	193	196	201	201	226	232	228	234	261	262	240	257	267	262	276	273	271	303	1.76	
Fruits and vegetables	408	429	428	444	437	457	490	476	472	500	521	522	552	535	561	552	592	606	657	656	679	715	731	751	756	769	783	837	1.88	
Fresh fruits	127	133	127	137	133	144	153	150	149	152	163	160	178	171	187	182	195	202	222	220	232	247	261	270	274	284	288	314	2.24	
Fresh vegetables	118	127	127	132	135	137	147	143	145	149	159	162	175	172	183	175	193	190	212	209	210	224	226	236	240	247	254	274	2.09	
Processed fruits	93	97	100	96	93	96	110	102	101	113	115	116	116	108	110	106	109	112	116	118	113	116	114	115	109	108	109	112	1.16	
Processed vegetables	70	72	74	79	78	76	86	84	84	84	84	84	84	84	84	84	84	84	84	84	84	84	84	84	84	84	84	84	1.30	
Other food at home	746	815	814	827	825	856	889	858	858	896	927	952	970	999	1075	1158	1212	1241	1305	1343	1278	1353	1380	1412	1382	1419	1442	1568	1.90	
Sugar and other sweets	94	101	102	113	105	112	114	114	109	112	117	116	117	119	128	119	125	124	129	141	132	144	147	143	139	155	148	150	1.65	
Fats and oils	68	72	72	78	79	82	83	81	77	84	83	87	85	86	89	85	86	91	104	102	103	110	114	117	115	111	111	117	1.63	
Miscellaneous foods	336	375	384	365	362	377	391	403	388	420	437	455	472	490	550	609	627	650	680	715	667	690	699	728	702	726	734	824	2.16	
Nonalcoholic beverages	213	224	213	225	233	240	252	245	231	242	250	256	254	268	286	306	322	333	342	337	333	361	370	384	375	374	393	423	1.76	
Food prepared by consumer unit on out-of-town trips	35	42	43	46	46	45	49	52	53	39	40	38	41	36	41	41	43	43	49	49	43	48	50	42	51	52	55	56	1.49	
Food away from home	1811	1620	1631	1664	1698	1702	1823	1921	2030	2116	2137	2235	2276	2211	2434	2634	2694	2668	2698	2619	2505	2620	2678	2625	2787	3008	3154	3365	1.66	
Alcoholic beverages	293	297	301	268	278	277	309	309	309	309	318	372	349	376	391	459	428	497	457	444	435	452	456	451	445	463	515	558	1.76	
Housing	8703	9251	9171	11272	11077	11272	11713	10457	10747	11272	11077	12023	13023	13293	13432	13918	11671	16366	16925	17107	16895	16557	16803	16887	17448	17798	18409	18886	19984	2.12
Shelter	4836	5191	5411	5415	5686	5926	6064	6344	6680	7016	7114	7602	7829	7887	7998	8805	9673	10023	10183	10075	9812	9825	9891	10080	10491	10742	11128	11895	2.22	
Owned dwellings	2953	3280	3310	3331	3492	3749	3783	3935	4245	4525	4602	4979	5165	5263	5324	5595	6516	6730	6760	6543	6277	6148	6056	6108	6149	6210	6295	6947	2.10	
Mortgage interest and charges	1817	1932	1968	1878	1919	2104	2114	2225	2455	2547	2639	2862	2962	2954	2936	3317	3753	3890	3826	3594	3351	3184	3067	3078	2953	2859	2889	3265	1.57	
Property taxes	597	789	782	825	922	930	939	971	1015	1123	1139	1233	1242	1344	1391	1541	1649	1709	1758	1811	1814	1845	1836	1848	1903	1913	1969	2065	3.20	
Maintenance, repairs, insurance, other expenses	540	559	560	628	651	715	729	738	775	854	829	884	960	965	997	1101	1115	1131	1176	1138	1112	1120	1153	1182	1293	1438	1437	1616	2.26	
Rented dwellings	1533	1588	1761	1714	1799	1788	1864	1983	1978	2027	2034	2134	2160	2179	2201	2345	2590	2602	2724	2860	2900	3029	3186	3324	3631	3802	4035	4167	2.48	
Other lodging (Hotels, etc.)	349	323	340	370	395	391	417	428	458	465	478	489	505	445	473	502	567	691	698	672	635	648	649	649	710	730	798	782	2.09	
Natural gas	246	250	252	279	283	268	291	301	284	270	307	411	330	392	424	473	509	480	531	483	440	420	359	393	439	421	355	381	1.73	
Electricity	758	803	787	809	821	808																								

Appendix 4. CPI-Adjusted Household Expenditures

Consumer Price Index: 1990 - 2017

CPI Category	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2015/1990
Food	132	136	138	141	144	148	153	157	161	164	168	173	176	180	186	191	195	203	214	218	220	228	234	237	243	247	248	250	1.9
Cereals_and_bakery_products	140	146	152	157	163	168	174	178	181	185	188	194	198	203	206	209	213	222	245	253	250	260	268	270	271	274	273	272	2.0
Meats_poultry_fish_and_eggs	130	133	131	136	137	139	145	149	147	148	155	161	162	169	182	185	187	196	205	204	208	223	231	236	253	260	248	246	2.0
Eggs	124	121	108	117	114	121	142	140	135	128	132	136	138	157	167	144	151	195	223	190	193	210	217	224	243	286	226	204	2.3
Poultry	133	132	131	137	142	144	152	157	157	158	160	165	167	169	182	185	182	191	201	204	204	210	221	232	236	237	231	231	1.8
Fish and Seafood	147	148	152	157	164	172	173	177	182	185	190	191	188	190	194	200	210	219	232	241	243	260	267	273	289	286	284	288	2.0
Other meats	127	132	132	134	137	139	144	148	147	148	152	156	162	166	173	178	181	185	191	195	195	207	211	211	219	228	226	224	1.8
Pork	130	134	128	132	134	135	148	156	149	146	157	162	162	165	174	178	177	181	185	181	190	206	207	209	228	219	210	211	1.7
Beef and veal	129	132	132	137	136	135	135	137	137	139	148	161	161	175	195	200	202	211	221	218	225	247	263	268	301	323	302	298	2.5
Dairy_and_related_products	126	125	129	129	132	133	142	146	151	160	161	167	168	168	180	182	181	195	210	197	199	213	217	218	225	222	217	217	1.8
Fruits_and_vegetables	149	156	155	159	165	178	184	187	198	203	205	212	221	226	233	241	253	263	279	273	273	285	283	290	294	294	296	296	2.0
Other_food_at_home	123	127	129	130	136	141	143	147	151	153	156	160	161	163	165	167	170	173	184	191	191	197	205	205	206	209	210	210	1.7
Food_away_from_home	133	138	141	143	146	149	153	157	161	165	169	174	178	182	188	193	199	207	216	223	226	231	238	243	249	256	263	269	1.9
Alcoholic_beverages	129	143	147	150	152	154	159	163	166	170	175	179	184	187	192	196	201	207	214	221	223	227	231	235	237	240	243	245	1.9
Housing	129	134	138	141	145	149	153	157	160	164	170	176	180	185	190	196	203	210	216	217	216	219	223	227	233	238	244	251	1.9
Shelter	140	146	151	156	161	166	171	176	182	187	193	201	208	213	219	224	232	241	247	249	248	252	257	263	271	279	288	298	2.0
Household_energy	105	107	108	111	112	112	115	118	114	114	123	135	127	138	144	162	177	182	201	188	189	194	189	194	202	195	191	198	1.9
Household_furnishings_and_operations	113	116	118	119	121	123	125	125	127	127	128	129	128	126	125	126	127	127	128	129	125	125	126	125	123	123	122	121	1.1
Apparel	124	129	132	134	133	132	132	133	133	131	130	127	124	121	120	120	119	119	119	120	119	122	126	127	128	126	126	126	1.0
Transportation	101	98	94	91	93	95	98	100	101	102	103	105	106	108	109	109	111	111	113	114	113	113	115	115	116	116	117	119	1.1
New_and_used_motor_vehicles	102	99	95	92	96	99	101	101	100	100	101	101	99	96	94	96	96	94	93	93	97	100	101	101	101	101	100	99	1.0
Gasoline_all_types	101	99	99	98	98	100	106	106	92	100	129	124	116	135	160	195	220	238	277	202	239	302	311	303	291	212	188	212	2.1
Medical_care	163	177	190	201	211	221	228	235	242	251	261	273	286	297	310	323	336	351	364	376	388	400	415	425	435	447	464	475	2.7
Recreation	101	98	94	91	93	95	98	100	101	102	103	105	106	108	109	109	111	111	113	114	113	113	115	115	116	116	117	119	1.1
Services_less_medical_care_services	137	143	148	154	158	164	169	174	178	183	189	197	203	209	215	221	230	237	245	248	250	254	258	265	271	278	285	293	2.0
Education_and_communication	96	92	89	86	89	92	95	98	100	101	103	105	108	110	112	114	117	120	124	127	130	131	134	136	138	138	139	137	1.4
All_items_less_shelter	128	133	137	141	145	149	153	156	157	160	166	170	171	175	179	186	192	197	205	203	209	217	221	224	226	223	224	227	1.7

Source: Bureau of Labor Statistics. <https://www.bls.gov/cpi/>

CPI-Adjusted Household Expenditures

Item	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Number of consumer units (in thousands)	96968	97918	100019	100049	102210	103123	104212	105576	107182	108465	109367	110339	112108	115356	116282	117356	118843	120171	120770	120847	121107	122287	124418	125670	127006	128437	129549	130001	1.32	
Income before taxes	31899	33901	33854	34688	36184	38014	39928	41762	43951	44649	47607	49430	51128	54453	58712	62531	63091	63685	62481	63665	65596	63784	66877	74664	73573	74664	73573	74664	73573	74664
Average annual expenditures	28381	29614	29846	30692	31731	32264	33797	34819	35535	36995	38045	39518	40677	40817	43395	46409	48400	49638	50446	49067	48109	49705	51442	51100	53495	55978	57311	60060	1.97	
Food	4296	4271	4273	4399	4411	4505	4698	4801	4811	5031	5158	5321	5375	5340	5781	5931	6111	6133	6443	6372	6129	6458	6599	6602	6759	7023	7203	7279	1.63	
Food at home	2485	2651	2643	2735	2712	2803	2876	2880	2780	2915	3021	3086	3099	3129	3347	3297	3417	3465	3744	3753	3624	3838	3921	3977	3971	4015	4049	4363	1.62	
Cereals and bakery products	368	404	411	434	429	441	447	453	425	444	452	445	442	461	445	446	460	506	507	506	502	531	538	544	519	518	524	564	1.41	
Cereals and cereal products	129	145	141	160	162	165	166	161	146	160	156	156	154	143	143	143	143	143	170	173	165	175	182	185	176	172	172	176	1.33	
Bakery products	240	259	270	274	267	276	281	292	278	288	297	296	296	292	307	302	304	317	337	334	337	356	356	359	343	346	353	388	1.44	
Meats, poultry, fish, and eggs	668	709	697	734	732	752	737	743	723	749	795	828	798	825	880	764	797	777	846	841	784	832	852	856	892	896	890	944	1.34	
Beef	218	228	210	234	227	228	215	224	218	220	238	248	231	246	265	228	236	216	239	226	217	223	226	219	232	245	244	253	1.12	
Pork	132	144	156	154	156	156	157	146	157	167	167	177	167	171	181	153	157	150	163	168	149	162	166	170	177	165	169	181	1.25	
Other meats	99	102	94	98	94	98	92	97	101	102	102	102	102	108	108	103	103	110	112	112	112	112	112	112	112	112	124	120	1.28	
Poultry	108	122	123	131	137	138	144	145	137	136	145	152	144	145	156	134	141	142	159	154	138	154	159	170	172	172	172	186	1.59	
Fish and seafood	82	81	77	87	89	87	88	89	98	106	110	114	114	124	128	111	122	122	135	117	121	122	122	129	126	130	140	154	1.54	
Eggs	30	31	28	30	30	30	34	33	32	34	35	32	34	35	42	33	37	42	43	51	44	46	50	53	56	58	63	56	1.20	
Dairy products	295	294	302	295	289	297	312	314	301	322	325	332	328	328	371	378	368	387	430	406	380	407	419	414	423	413	410	450	1.40	
Fresh milk and cream	140	129	134	128	127	123	132	128	120	122	131	136	127	127	144	146	140	154	168	144	141	150	152	152	147	140	139	147	1.00	
Other dairy products	155	165	168	167	162	174	180	186	181	200	193	196	201	201	226	232	228	234	261	262	240	257	267	262	276	273	271	303	1.76	
Fruits and vegetables	408	429	428	444	437	457	490	476	472	500	521	522	552	535	561	552	592	600	657	656	679	715	731	751	757	763	779	783	837	1.88
Fresh fruits	127	133	127	137	133	144	153	150	149	152	163	160	178	171	187	182	195	202	222	220	232	240	247	261	270	274	284	288	314	2.24
Fresh vegetables	118	127	127	132	135	137	147	143	145	149	159	162	175	172	183	175	193	190	212	209	210	224	226	236	240	247	254	274	2.09	
Processed fruits	93	97	100	96	93	96	110	102	101	113	115	116	116	116	108	110	108	110	112	116	118	113	116	114	115	109	108	109	112	1.16
Processed vegetables	70	72	74	79	76	80	80	80	76	86	86	84	84	82	89	85	95	96	107	110	124	129	130	130	130	133	130	133	137	1.07
Other food at home	746	815	814	827	825	856	889	895	858	896	927	952	970	999	1075	1158	1212	1241	1305	1343	1278	1353	1380	1412	1382	1419	1442	1568	1.90	
Sugar and other sweets	94	101	102	113	105	112	114	114	109	112	117	116	117	116	119	128	119	125	124	129	141	132	144	147	143	139	155	148	150	1.65
Fats and oils	68	72	72	78	79	82	83	81	77	84	83	87	85	86	89	85	86	91	104	102	103	110	114	117	115	111	111	117	1.63	
Miscellaneous foods	336	375	384	365	362	377	391	403	388	420	437	455	472	490	550	609	627	650	680	715	667	690	699	728	702	726	734	824	2.16	
Nonalcoholic beverages	213	224	213	225	233	240	252	245	231	242	250	256	254	268	286	303	332	333	342	337	333	361	370	384	375	374	393	423	1.76	
Food prepared by consumer unit on out-of-town trips	35	42	43	46	46	45	49	52	53	39	40	38	41	36	41	41	43	43	49	49	43	48	50	42	51	52	55	56	1.49	
Food away from home	1811	1620	1631	1664	1698	1702	1823	1921	2030	2116	2137	2235	2276	2211	2434	2634	2694	2668	2698	2619	2505	2620	2678	2625	2787	3008	3154	3365	1.66	
Alcoholic beverages	293	297	301	288	278	277	309	309	318	372	349	376	391	459	426	497	452	444	435	412	456	451	445	445	463	515	484	558	1.76	
Housing	8703	9252	9477	9636	10106	10458	10747	11272	11713	12057	12319	13011	13283	13432	13918	15167	16366	16920	17109	16895	16557	16803	16887	17148	17798	18409	18886	19884	2.12	
Shelter	4836	5191	5414	548	584	598	636	668	682	707	702	789	782	798	865	963	1002	1018	1028	1018	1028	1018	1028	1018	1028	1018	1028	1018	1028	1.98
Owned dwellings	2953	3280	3310	3331	3492	3749	3783	3935	4245	4525	4640	4979	5165	5263	5324	5958	6516	6790	6760	6543	6277	6184	6056	6108	6149	6210	6295	6947	2.10	
Mortgage interest and charges	1817	1932	1968	1878	1919	2104	2114	2225	2455	2547	2639	2862	2962	2954	2936	3317	3753	3890	3826	3594	3351	3184	3067	3078	2953	2859	2899	3265	1.57	
Property taxes	597	789	782	825	822	930	939	971	1015	1123	1139	1233	1242	1344	1391	1541	1649	1709	1758	1811	1814	1845	1836	1848	1903	1913	1969	2065	3.20	
Maintenance, repairs, insurance, other expenses	540	559	560	628	651	715	729	738	775	854	825	884	960	965	997	1101	1115	1131	1176	1138	1112	1120	1153	1182	1293	1438	1437	1616	2.26	
Rented dwellings	1533	1588	1761	1714	1799	1788	1864	1983	1978	2027	2034	2134	2160	2179	2201	2345	2590	2602	2724	2860	2900	3029	3186	3324	3631	3802	4035	4167	2.48	
Other lodging (Hotels, etc.)	349	323	340	370	395	391	417	426	458	465	478	489	505	445	473	502	567	691	698	672	635	648	649	649	710	730	798	782	2.09	
Natural gas	246	250	252	279	283	268	291	301	284	270	307	311	330	392	424	473	509	480	531	483	440	420	359	393	439	421	355	381	1.71	
Electricity	758	803	787	836	861	869	907	909	921	899	911	1009	981	1028	1064	1155	1286	1303	1353	1377	1413	1423	1388	1422	1484	1460	1444	1420	1.93	
Fuel oil and other fuels	100	102	92	99	98	86	108	108	85	74	97</																			

Appendix 6. Definitions of Subcategories and underlying products or services

Subcategories	Products
TOTAL	Sum of all categories of household consumption
EatingOut	Elementary and second school lunch Higher education school lunch Meals at limited service eating places Meals at restaurants Meals at hotels Meals at other retailers Meals at drinking places Alcohol in purchased meals
AlcoholicBeverages	Spirits Wine Beer
CerealsBakeryProducts	Cereals Bakery products
MeatsPoultryFishEggs	Beef and veal Pork Eggs Poultry Other meats Fish and seafood
DairyProducts	Fresh milk Processed dairy products
FruitsVegetables	Fruit (fresh) Vegetables (fresh) Processed fruits and vegetablesfruit and vegetable juices
OtherFood	Fats and oils Sugar and sweets Coffee, tea and other beverage materials Mineral waters, soft drinks
Shelter	Home construction
OtherLodging	Hotels and motels Housing at schools Other delivery services (by non-U.S. postal facilities) Funeral and burial services Hairdressing salons and personal grooming establishments Miscellaneous personal care services Laundry and dry-cleaning services Clothing repair, rental and alterations Repair and hire of footwear Child care Social assistance Child care Individual and family services Vocational rehabilitation services Community food and housing/emergency/other relief services
Utilities	Electricity, natural gas, water, refuse, sewage and other household utilities. There are broken out in more detail in the Energy section of the report

HouseholdOperations	Domestic services Moving, storage and freight services Repair of furniture, furnishings and floor coverings Repair of household appliances Other household services
HousekeepingSupplies	Household cleaning products Household paper products Household linens Sewing items Miscellaneous household products
HouseholdTextiles	Window coverings
Furniture	Furniture Clocks, lamps, lighting fixtures, and other household decorative items
FloorCoverings	Carpets and other floor coverings
MajorAppliances	Major household appliances (Refrigerator, washer machine, dishwasher, HVAC)
MiscHousewares	Small electric household appliances Dishes and flatware Non-electric cookware and tableware
MiscEquipment	Tools, hardware, and supplies Outdoor equipment and supplies
Apparel	Luggage and similar personal items Jewelry Watches Men's and boy's clothing Women's and girl's clothing Children's and infant's clothing Clothing materials Standard clothing issued to military personnel Shoes and other footwear
EntertainmentGoods	Televisions Other video equipment Audio equipment Prerecorded and blank audio discs/tapes/digital files/downloads Video cassettes and disc, blank and prerecorded Photographic equipment Personal computers and peripheral equipment Computer software and accessories Calculators, typewriters, and other information processing equipment Sporting equipment, supplies, guns, and ammunition Motorcycles Bicycles and accessories Pleasure boats Pleasure aircraft Other recreational vehicles Musical instruments Telephone and facsimile equipment Games, toys and hobbies Pets and related products Flowers, seeds, and potted plants

	<ul style="list-style-type: none"> Film and photographic supplies Land line, telephone services, local charges Land line, telephone services, long-distance charges Cellular telephone services First class postal services (by USPS) Internet access
PersonalCareProducts	<ul style="list-style-type: none"> Household cleaning products Household paper products Household linens Sewing items Miscellaneous household products Hair, dental, shaving, and misc. personal care products, excluding electrical products Cosmetics/perfumes/bath/nail preparations and implements Electric appliances for personal care
TobaccoSmokingSupplies	Tobacco product manufacturing
VehiclePurchases	<ul style="list-style-type: none"> New domestic autos New foreign autos New light trucks Net purchases of used autos Net purchases of used light trucks
MotorVehicleFuels	Gasoline and other vehicle fuels
OtherVehicleExpenses	<ul style="list-style-type: none"> Tires Accessories and parts Motor vehicle maintenance and repair Motor vehicle rental Auto leasing Truck leasing Parking fees and tolls
AirTravel	Air travel
PublicTransportation	Public transportation
Healthcare	<ul style="list-style-type: none"> Physician services Dental services Home health care Medical laboratories Specialty outpatient care facilities and health and allied services All other professional medical services Nonprofit hospitals services Proprietary hospitals services Government hospitals services Non-profit nursing homes' services Proprietary and government nursing homes services Physician services Home health care Other paramedical services Hospital services Nursing homes Home for the elderly Residential mental health and substance abuse

	<p>Other residential care facilities Therapeutic medical equipment Corrective eyeglasses and contact lenses Pharmaceutical products Other medical products Net medical care and hospitalization insurance</p>
EntertainmentServices	<p>Membership clubs and participant sport centers Motion picture theaters Live entertainment, excluding sports Spectator sports Museums and libraries Amusement parks, campgrounds, and related recreational services Cable and satellite television and radio services Video media rental Photo processing Photo studios Repair of audio-visual, photographic and information processing equipment Veterinary and other services for pets Package tours Maintenance and repair of recreational vehicles and sports equipment Gambling</p>
PersonalServices	<p>Hairdressing salons and personal grooming establishments Miscellaneous personal care services Laundry and dry-cleaning services Clothing repair, rental and alterations Repair and hire of footwear Child care Social assistance Child care Individual and family service Vocational rehabilitation services Community food and housing/emergency/other relief services Net income loss insurance Net workers' compensation insurance Net motor vehicle and other transportation insurance Legal services Accounting and other business services Labor organizations' services Professional associations' services Labor unions and political organizations Professional associations All other similar organizations, excluding condo. and homeowners associations Legal services</p>
Reading	<p>Books Newspapers and periodicals Stationery and miscellaneous printed materials</p>
Education	<p>Proprietary and public higher education Nonprofit private higher educational services Elementary and secondary schools Day care and nursery schools</p>

	Commercial and vocational schools Nursery schools Elementary and secondary schools Private higher education Other education and research
Miscellaneous	Hotels and motels Housing at schools Other delivery services (by non-U.S. postal facilities) Funeral and burial services
CashContributions	Social advocacy and civic and social organizations Religious organizations' services Foundations and grant making and giving services Religious organizations Grant making and giving services Social advocacy Civic and social organizations
InsurancePensions	Financial services indirectly measured, commercial banks Financial services indirectly measured, other financial institutions Financial services' charges and fees Direct commissions, exchange-listed equities Direct commissions, other equity securities Indirect commissions, over-the-counter equity securities Indirect commissions, other equity securities Mutual fund sales charges Portfolio management and investment advice services Trust, fiduciary, and custody activities Pension services Life insurance services Net household insurance