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Enabling Low Carbon Communities: The Roles of Smart Planning Tools and Place-Based Solutions

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Enabling Low Carbon Communities:
The Roles of Smart Planning Tools and Place-Based Solutions

By

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Committee in charge:

Professor Daniel M. Kammen, Chair
Professor David Anthoff
Professor Joan Walker
Professor Stephen Wheeler

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Abstract

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The scale of the climate crisis is immense and solutions are urgently needed. This dissertation develops tools to provide highly tailored carbon footprint information and place-based solutions to U.S. households and communities in three complimentary studies. The first study quantifies the greenhouse gas (GHG) savings potential of different U.S. metropolitan areas and household types within locations, developing average household carbon footprint (HCF) profiles for 28 metropolitan areas, 6 household sizes and 12 income brackets. The model includes emissions embodied in transportation, energy, water, waste, food, goods, and services, and further quantifies GHG and financial savings from potential mitigation actions across all locations and household types. The size and composition of carbon footprints vary dramatically between geographic regions (38 to 52 tCO_2e) and within regions based on basic demographic characteristics (<20 to >80 tCO_2e). Despite these differences, large cash-positive carbon footprint reductions are evident across all household types and locations.

Using national household surveys, the second study develops econometric models to estimate HCF for essentially all U.S. zip codes, cities, counties, and metropolitan areas. The results demonstrate consistently lower HCF in urban core cities (~40 tCO_2e) and higher carbon footprints in outlying suburbs (~50 tCO_2e), with a range from ~25 to >80 tCO_2e in the 50 largest metropolitan areas. In contrast to a vast literature demonstrating GHG savings in more dense cities, analysis of all U.S. locations presents a more complex picture. Population density exhibits a weak but positive correlation with HCF until a density threshold is met, after which range, mean, and standard deviation of HCF decline. While population density contributes to relatively low HCF in the central cities of large metropolitan areas, the more extensive suburbanization in these regions contributes to an overall net increase in HCF compared to smaller metropolitan areas. Suburbs alone account for ~50% of total U.S. HCF.

Results from this quantitative research have informed the development of “smart” online carbon

management tools that allow users to quickly calculate, compare and manage household carbon footprints, and to visualize average community carbon footprints using high spatial resolution interactive maps. Yet, the potential benefits of such tools are limited to those who find them, and the information may often do little to increase intrinsic motivation to adopt new low carbon technologies and practices. Following lessons from behavioral sciences, a subsequent study engaged ~2,700 residents in eight participating cities to track and reduce household carbon footprints and compete for the title of "Coolest California City." The yearlong pilot project achieved an estimated 14% reduction in electricity consumption, lending evidence that community-scale climate initiatives, enabled by sophisticated information and communication technologies and motivated local program implementers, can help scale up tailored, place-based climate solutions. Together, this research and accompanying tools and programs provide a framework for individuals and communities to prioritize GHG mitigation opportunities and stimulate collective climate action.

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AB 32	Assembly Bill 32, California State
BEA	U.S. Bureau of Economic Analysis
BLS	U.S. Bureau of Labor Statistics
BTS	U.S. Bureau of Transportation Statistics
Btu	British thermal unit(s)
ARB	California Air Resources Board
CAP	Climate Action Plan
CFC	chlorofluorocarbon
CH_4	methane
CO_2	carbon dioxide
CO_2e	carbon dioxide equivalent
EIA	U.S. Energy Information Administration
EPA	U.S. Environmental Protection Agency
FTE	full time employee
g	gram(s)
GHG	greenhouse gas
GWP	Global Warming Potential
HV/AC	heating, ventilating, and air conditioning
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
J	joule
kg	kilogram(s)
kWh	kilowatt-hour(s)
lb(s)	pound(s)
LFG	landfill gas
MMBtu	one million British thermal units
mpg	miles per gallon
mt	metric ton(s)
MWh	megawatt-hour(s)
t	metric ton(s)
VMT	Vehicle miles traveled
WBCSD	World Business Council for Sustainable Development
WRI	World Resources Institute

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ERG Professor Emeritus Dick Norgaard opened my eyes to climate change and the social factors contributing to its causes and potential solutions, and for that I will be forever grateful. Professor Isha Ray generously acted as instructor of record and esteemed advisor for the course, Behavior and Sustainability, that my colleague Joe Kantenbacher and I ran for three semesters. Professor John Harte provided important insights on the econometric analysis in Chapter four. Other ERG core faculty provided guidance and insights along the way, including Gene Rocklin, Duncan Callaway and the late Alex Farrell.

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Finally, I am eternally grateful to my wife, Eva. Her support has been immeasurable. I hereby confer upon her title of "Coolest California Wife."

Chapter 1: Introduction

1.1. Motivation

Climate change is a massive moral dilemma. Humanity has already warmed the planet to the point where natural disasters are more common and destructive, and people are suffering and dying as a result. This is just the beginning. The speed and scale of suffering will only increase in coming decades. Ecosystems are increasingly disrupted, or disappearing entirely, and those who are the least responsible for the problem are the least likely to be able to adapt these changes, and the most likely to suffer the consequences.

From a moral perspective we clearly do not have the right to cause the suffering of others. Yet virtually everything we do, and every dollar we spend, adds more greenhouse gases to the atmosphere, exacerbating climate change and its consequences. As young people get older the demands of career and family tend to push their carbon footprints higher and lock them into lifestyles that are often very difficult to change. Hence, the moral dilemma. How can we live productive lives while minimizing our contribution to this very real threat to human wellbeing?

There are alternatives. The average European carbon footprint is less than one half that of the average American's (Roelich et al. 2014) and a few hundred dollars could purchase enough carbon offsets to essentially eliminate the rest. Many American households live at or below the European average already (Weber and Matthews 2008), even at higher income levels, which tend to correlate strongly with carbon footprints.

Solutions are possible, but change is slow. The European case is the result of decades of top down policy, bottom-up lifestyle changes and "middle out" innovations in technology that help enable lower carbon lifestyles. But what works well in European countries may not be at all appropriate or feasible in the U.S. or China, Ghana or elsewhere. A large and diverse range of solutions is urgently needed for heterogeneous populations, businesses, communities and governments, with vastly different mitigation opportunities, motivations, barriers, priorities and capacity to make change.

Until virtually all energy is produced from renewable sources and remaining emissions are safely sequestered back into the earth, there will be a need to scale up tailored solutions to diverse populations.

1.2. Goals

The purpose of my research is to improve the decision-making capacity of individuals, organizations and local governments interested in reducing their contributions to climate change, and to explore ways of motivating those who are less motivated. This dissertation incorporates lessons from over a decade of research, software development, program development, teaching and outreach at the CoolClimate Network, a division of the Renewable and Appropriate

Laboratory at U.C. Berkeley. Each of these areas of work informs and supports the others and contributes toward the projects' goals. This dissertation focuses on three interrelated projects that explore the use of information technology to help enable the adoption of low carbon solutions for U.S. households and communities. In particular, I examine the following questions:

1. What are the primary drivers of U.S. household carbon footprints?
2. How do U.S. household carbon footprints vary at different spatial scales (zip codes, cities, counties, metropolitan, state, regional scales)?
3. How do GHG reduction opportunities vary by location and demographic characteristics?
4. What is the effect of population density on U.S. household carbon footprints at different geospatial scales?
5. What is the potential of an inter-city carbon footprint reduction competition to reduce household carbon footprints? What motivates participants with different demographic and political orientations? Who performs better? What lessons can help inform the development of future similar programs?

1.3. Contributions

This dissertation makes the following contributions to academic literature:

1. I characterize typical household carbon footprints and GHG mitigation opportunities for different household types by location, household size and income. Previous studies have quantified greenhouse gas (GHG) emission reduction potentials of U.S. households, e.g., Dietz et al. (2009) and Laitner and Ehrhardt-Martinez (2009). This is the first study to quantify GHG savings potential in different U.S. cities and household types within cities. Large differences between household types highlights the need for tailored GHG mitigation policies and programs. The carbon footprint management software developed to accompany this research is designed to aid in this effort, and indeed is widely used for research, teaching and program development.
2. I examine the primary drivers of household carbon footprints. Of the 37 independent variables in the multivariate regression model, 6 explain 93% of the variation. I argue that the location of homes and the size of homes are two critical levels for policymakers to control greenhouse gas emissions.
3. I analyze the effect of population density on household carbon footprints at high spatial resolution for all U.S. locations. This is the first analysis of average household carbon footprints for all U.S. locations, providing insights into which GHG mitigation opportunities may be more promising for different locations. In particular, I suggest that population density has very different implications for urban cores, suburbs and metropolitan regions as a whole.
4. Through the design, implementation and evaluation of an inter-city carbon footprint reduction competition I demonstrate how information technology, combined with on-the-ground program development, can help scale up GHG mitigation to diverse

populations. This is the first published case study of an inter-community GHG reduction competition.

5. This research, and accompanying software tools and programs, provides a framework for individuals and communities to prioritize GHG mitigation opportunities and stimulate collective climate action.

1.4. Dissertation structure

Chapter 2 develops an argument for the need for place-based solutions by reviewing strengths and weaknesses of existing climate policy and urban planning. Chapter 3 quantifies GHG reduction opportunities for different household types in 28 U.S. metropolitan areas. This project demonstrates the need to tailor GHG mitigation opportunities to different household types and locations. Chapter 4 uses national survey data and econometrics to estimate average household carbon footprints for every U.S. zip code, city, county and state. The study analyzes the effects of population density on household carbon footprints in cities of different size in urban cores, suburbs and rural areas. The findings of these first two studies provide detailed information on the size and composition of household carbon footprints. This information has been developed into “smart” online carbon management tools for households and communities. Yet information alone may do little to change behavior. Effective behavior change programs utilize a number of techniques to engage, educate, motivate and enable change. Chapter 5 reviews behavior theories relevant to the design of energy reduction interventions, with an emphasis on competitions. Chapter 6 includes methods, results and conclusions from designing, implementing and evaluating the CoolCalifornia Challenge, a competition engaging nearly 2,700 households in eight California cities to track and reduce household carbon footprints. This pilot project serves to demonstrate the use of information technology to help scale up tailed GHG mitigation strategies to diverse populations. Chapter 7 concludes with a summary of major findings and a roadmap for future research.

Chapter 2. Background

2.1. Overview

The scale of the climate crisis is immense. Essentially every activity that humans take results in the release of greenhouse gases to the atmosphere. Our transportation, housing, food, goods and services are all powered by fossil fuels and industrial activities that contribute to a warming planet. Yet each person, household, business and community is different, with varying contributions to emissions as well as opportunities, priorities, abilities and motivations to reduce them.

The primary thesis of this dissertation is that highly tailored information, tools and policies are needed to scale up the adoption of low carbon technologies and practices to a wide range of actors. While international and national market-based policies, regulation and technology development clearly need to play the dominant role in climate change mitigation, there are limits to their effectiveness without simultaneously driving consumer demand for solutions. There is a need for a more nuanced, place-based application of planning, policy and behavioral approaches that consider the unique characteristics of populations and locations. Communities play a key role in scaling up decentralized decision-making since cultural, demographic, attitudinal, geographic and political contexts are more similar at fine geographic scales, and social interactions play an important role in motivating sustainable behavior (Jackson 2004) (Stern 2000).

This chapter develops a theoretical basis for work in chapters three and four. It explores research on the scale of the climate crisis, the necessity and potential limitations of centralized policymaking, and the roles of local climate action planning and decision-making. Considered together, this work suggests the need for smart planning and decision-making tools and highly tailored, place-based policies. The research developed in chapters three and four has led to the development of "smart" GHG management software for households and communities. These tools provide comparative feedback and can help communities prioritize and quantify opportunities to reduce GHG impacts. Yet information tools are clearly insufficient to help massively scale up the adoption of low carbon technologies and practices. There is a need to understand the drivers of human behavior and to design, test and implement programs to directly engage households in climate action at sufficient scale. Chapter 5 reviews relevant behavioral theories that informed the design of a pilot GHG reduction program in eight communities across California.

2.2. The scale of the climate crisis

The 2014 IPCC assessment report, AR5 (Intergovernmental Panel on Climate Change 2014), estimates that global GHG emissions need to be reduced between 41% and 72% from 2010 levels by 2050 to be *likely* to keep warming under 2 degrees C (Edenhofer et al. 2014) and emissions need to be virtually eliminated by the end of the century. Key risks with large magnitude, high probability and/or irreversible impacts include: mortality and morbidity from extreme heat, breakdown of food production systems and subsequent food insecurity, decreasing availability of water, loss of marine ecosystem services, and inland flooding with severe risks to human health and livelihoods (Field et al. 2014), among other risks. Losses of human life and wellbeing will be greater for the poor, who are the least responsible for the problem, making this a massive global moral dilemma and social injustice.

Developed countries, led initially by the G-8 and the European Union have set reduction targets at 80% below 1990 levels by 2050. Such reduction would do much to correct the climate injustice and slow the pace of warming; however, there is no binding obligation to meet the targets. In the case of the United States, there has been a strong lack of political will to enact climate legislation and no clear roadmap to successfully achieve targets. Recent executive actions by the Obama Administration to limit emissions from power plants and motor vehicles are promising, but potentially reversible and insufficient to meet deep reduction targets.

Given lack of federal leadership, states and municipal governments have taken it upon themselves to curb emissions from the bottom-up (Wheeler 2008). For example, the state of California adopted the 80% reduction target under Executive Order S-3-05, signed by Governor Schwartzenneger in 2008. Several recent studies (Greenblatt 2014; Wei et al. 2013; Williams et al. 2012; Long et al. 2011) have developed and analyzed policy and technology scenarios for the California to meet these targets and have come to essentially the same conclusion: existing technologies and policies, even if fully deployed, are not sufficient to meet the target. Additional savings through conservation will be required (e.g., reducing miles driven, changing diets, and reducing waste) or else entirely new technologies will needed. Figure 1 shows the scale of technologies and practices needed for California to meet its 2050 GHG reduction target, reprinted from Wei et al. (2013). This implies massive adoption of low carbon technologies and practices by households and businesses throughout California, and policies commensurate with the scale of the problem to motivate massive adoption for diverse actors.

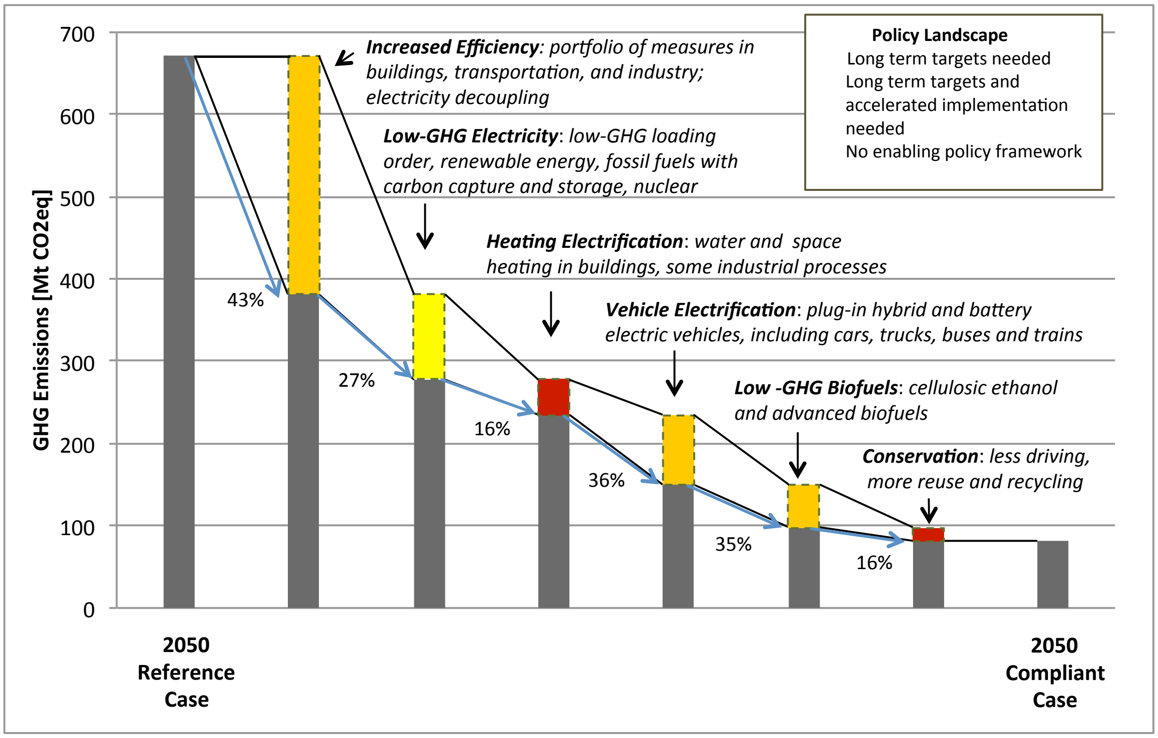

Figure 1. Technology pathway for California to meet 80% GHG reduction target by 2050 (Wei, et al., 2013)

2.3. The necessity and potential limitations of centralized climate policies

Aggressive national and subnational policies are necessary for any chance of averting the worst consequences of climate change. Yet climate policies currently proposed or even imagined are woefully insufficient to address the problem (Wheeler 2012).

Climate change has been described as a "super wicked problem" (Levin et al. 2012) in which time is running out, central authority to address the problem is weak, future costs are irrationally discounted, and the same actors responsible for the problem are those seeking to provide a solution. In such contexts, short-term planning and policy objectives are insufficient to address the problem at sufficient scale and speed. Any climate legislation is also subject to future cuts, modifications or reversals based on the state of political will, power and maneuvering in Washington (Lazarus 2008; Wheeler 2012). The nature of this problem creates a need for a wider range of solutions, including decentralized climate mitigation efforts.

Super wicked problems defy simplistic solutions. Many economists argue that simply internalizing the social cost of carbon could essentially solve the climate crisis. For example, Metcalf and Weisbach (2009) suggest that "a well-designed carbon tax can capture about 80% of U.S. emissions by taxing only a few thousand taxpayers, and almost 90% with a modest additional cost." Another recent unpublished study (Nystrom and Luckow 2014) by an advocacy group with a policy agenda to pass the proposal as national legislation, Citizens Climate Lobby, suggests a wellhead carbon tax, combined with border adjustments, and redistributing revenue through income taxes could cut GHG emissions by 60%, while increasing welfare for the poor and average American households.

There are a number of reasons why these, and similar studies, may overestimate the effect of carbon taxes and why carbon taxes may not be an optimal solution. First, the effect of price signals, or elasticity of demand, varies considerably from one sector to another and in some important sectors, like transportation, fuel price seems to have little effect. Previous U.S. studies on the elasticity of demand for gasoline have frequently relied on data from the 1970s and early 1980s oil crises, which reported an average long term elasticity of demand for gasoline of -0.5 to -0.7, i.e., a 1% increase in the price of gasoline would eventually lead to about an 0.6% decline in gasoline consumption. These estimates have found their way into GHG mitigation studies at the highest level, e.g., AR5 notes the long-term elasticity of demand for transportation fuels is -0.6 to -.08. However, evidence from the recent energy price hike calls the data into questions. Hughes, Knittle and Sperling (2006) first noted a dramatic shift in the short-term elasticity of demand for gasoline. Whereas short-term elasticity of demand was -0.21 to -0.34 for 1975 to 1980, elasticities were a mere -0.034 to -0.077 from 2001 to 2006. According to Hughes et al., low elasticity may be due to a number of factors including consumer preferences, lack of substitutes and structural forces. The energy crises were also accompanied by important historical and sociological phenomena, e.g., long lines at gas stations and the Iran hostage crisis, which did not accompany the recent changes in prices. As a result, in 1980 fuel economy was the most important consideration in new car purchases (Sutherland 1991).

Enough time has passed since the doubling of U.S. gasoline prices to take a preliminary look at the long-term (or at least medium-term) impact on demand of the change in gasoline prices. Figure 2 compares gasoline prices (U.S. Energy Information Administration 2014b) with long distance vehicles miles traveled and gasoline consumption per capita from 2002 through 20012 (U.S. Department of Energy 2014). Between 2002 and 2007 gasoline prices more than doubled and have remained between 1.6x and 2.4x for the last five years; however, vehicle miles traveled (VMT) decreased by only about 5%, while fuel consumption decreased by 12%, and both VMT and consumption have remained stable for the last five years. This suggests that a doubling of fuel prices may only lead to perhaps only a 10% reduction in fuel in the U.S. case, and not the 60% often assumed in carbon tax studies.

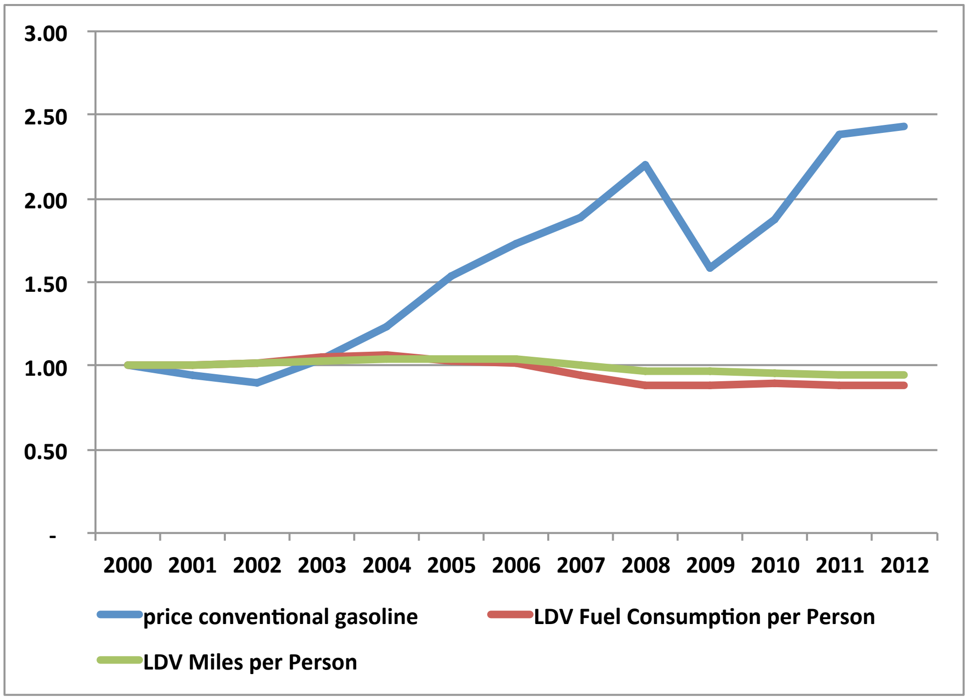

Figure 2. Gasoline prices (real USD) and long distance vehicle (LDV) miles and fuel consumption per capita

The GHG impact of a carbon tax depends on the elasticity of demand for taxed goods and services, as well as how tax revenues are used. A common, although misleading, argument against carbon taxes is that they are regressive, since the poor pay a larger portion of their incomes on fuel. Burtraw et al. (2009) compare a range of mechanisms to return carbon revenues back to the economy. Under cap and dividend, with revenues paid to households on a per capita basis, they estimate average households in the lowest two income deciles would gain $236 per year with a carbon price of $20/tCO$_2$, while average households would pay $132. Returning carbon tax revenues to consumers, by any mechanism, would weaken the CO_2 savings of the policy since the funds would subsequently be spent by consumers on goods and services (the rebound effect), and funds would not otherwise be invested in low carbon technologies or offsets, as is typical with cap-and-trade mechanisms.

The elasticity of demand for gasoline also suggests that a range of policy options will be needed to address climate change. For example, fuel economy standards may be more effective than carbon taxes at managing emissions from the transportation sector. Motor vehicles are end use consumer goods, similar to energy-consuming appliances, which have been very effectively regulated with efficiency standards, saving consumers an estimate $80 billion per year (Meyers et al. 2003). Urban planning is also an important mechanisms to lower vehicle miles driven and increase efficient vehicle technologies (Burchell et al. 1998).

International scientific consensus is now converging upon the reality that centralized policies, including market-based mechanisms, standards, regulation, and technology investments, may be insufficient to dramatically slow climate change on their own. In contrast to previous IPCC assessment reports, AR5 has a strong emphasis on the critical roles of behavior change, widespread adoption of energy efficient technologies and urban planning. In the Summary for

Policymakers, the document most widely read by decision-makers, three of the five mitigation areas covered have a strong focus on localized decision-making:

> SPM.4.2.1 Cross-sectoral mitigation pathways
>
> *Efficiency enhancements and behavioural changes, in order to reduce energy demand compared to baseline scenarios without compromising development, are a key mitigation strategy in scenarios reaching atmospheric CO2eq concentrations of about 450 or 500 ppm by 2100.*
>
> *Behaviour, lifestyle and culture have a considerable influence on energy use and associated emissions, with high mitigation potential in some sectors, in particular when complementing technological and structural change.*
>
> SPM.4.2.3 Energy end-use sectors
>
> *Technical and behavioural mitigation measures for all transport modes, plus new infrastructure and urban redevelopment investments, could reduce final energy demand in 2050 by around 40 % below the baseline.*
>
> *Lifestyle, culture and behaviour significantly influence energy consumption in buildings. A three-to five-fold difference in energy use has been shown for provision of similar building-related energy service levels in buildings. For developed countries, scenarios indicate that lifestyle and behavioural changes could reduce energy demand by up to 20 % in the short term and by up to 50 % of present levels by mid-century.*
>
> SPM.4.2.5 Human settlements, infrastructure and spatial planning
>
> *Infrastructure and urban form are strongly interlinked, and lock-in patterns of land use, transport choice, housing, and behaviour. Effective mitigation strategies involve packages of mutually reinforcing policies, including co-locating high residential with high employment densities, achieving high diversity and integration of land uses, increasing accessibility and investing in public transport and other demand management measures.*

These statements reflect an important shift in the focus of climate policy away from purely centralized decision-making toward localized actions that require high levels of information and technical capacity across a wide range of stakeholders (households, businesses, local and regional governments). In sum, the landscape for GHG mitigation has become more complex, requiring information at multiple scales (national, state, regional, local, individual), increased technical capacity and efforts to motivate a wide range of actors to adopt low carbon practices.

If decision-making needs to be improved at multiple scales, then better information is also required. It is helpful to consider that at any time, and for any entity (household, business, government etc.) there exists a set of measures that could be taken to reduce greenhouse gases. This concept is most popularly conceived as a greenhouse gas marginal abatement cost (MAC) curve, with total annual GHG savings on the x-axis (e.g., metric tons CO_2e^{-yr}) and the annual levelized cost per ton of CO_2 equivalent conserved on the y-axis ($/t$CO_2e^{-yr}$). The total abatement cost (or savings) is simply the sum of the area under the curve. MAC curves have traditionally been applied at global scales (Enkvist, Nauclér, and Rosander 2007), nations (Morris, Paltsev, and Reilly 2012) or sectors (Moran et al. 2011), but they may also theoretically be applied to individuals and organizations. These measures require varying degrees of cost, effort, expertise, information and motivation to identify and successfully implement.

In the absence of strong national climate policy, this dissertation seeks to help enable low carbon consumption for U.S. households. It builds on work from my 2005 Masters project (Jones 2005), which developed the first consumption-based carbon footprint calculator (CoolClimate Network 2014). The goal of this ongoing project has been to allow individuals and households to calculate their complete carbon footprints, compare their results to similar households (comparative feedback) and develop personalized climate action plans to reduce their impact and purchase carbon offsets to lead carbon neutral lifestyles. The project has evolved into an ecosystem of GHG management tools, programs and supporting research ("CoolClimate Network" n.d.).

2.4. Local climate action planning

Local greenhouse gas inventories and climate action plans (CAPs) have been the focus of increasing attention. A study by Wheeler (2008) of early CAPs highlighted the shortcomings of state and municipal plans and recommended five steps to improve the effectiveness of local climate action planning: 1) choosing stronger GHG reduction targets, 2) using a long-term planning framework to achieve targets, 3) including a full range of measures, 4) implementing plans more effectively, and 5) engaging in social marketing and educational efforts. These steps are highly consistent with work developed for this dissertation and complimentary work to develop a smart planning tool for community-scale greenhouse gas mitigation planning. Another somewhat more recent analysis of CAPs (Bassett and Shandas 2010) similarly concludes that there exists a wide range of formats, purposes and analysis in these reports. The most detailed plans with targets and implementation strategies include standard approaches in urban planning, e.g., public transit, energy codes and compact urban design. There is little evidence that CAPS include social marketing approaches, although some do mention the need for educational efforts.

One of the critical aspects of measurement and targets is the boundary selected for the approach, i.e., what emissions are included and excluded in the analysis. Several studies by Ramaswami and colleagues (Chavez and Ramaswami 2011; Hillman and Ramaswami 2010; Ramaswami et al. 2011) have analyzed different community-scale GHG inventory methodologies, including traditional production-based approaches, hybrid methods and consumption-based approaches. Each methodology provides a different lens by which cities may view, prioritize and implement GHG mitigation strategies. The consumption-based approach in ICLEI's U.S. Community Protocol for Accounting and Reporting Greenhouse Gas Emissions ("ICLEI USA" n.d.) was developed in collaboration with this dissertation research and includes the methods outlined in chapters three and four of this dissertation.

Consumption-based GHG accounting (Hertwich and Peters 2009; Weber and Matthews 2008; Wier et al. 2001) allocates all emissions to final demand, which includes households, governments and capital investments, accounting for 77%, 8% and 15% of U.S. emissions, respectively (Roelich et al. 2014). Roughly 80% of GHG emissions associated with final demand are from domestic production in the U.S. (Ghertner and Fripp 2007; Roelich et al. 2014; Weber and Matthews 2008) while remaining emissions are embodied in imported goods. Consumption-based accounting allocates emissions to final demand, regardless of where emissions physically enter the atmosphere. Under this accounting framework, businesses are in service to consumers, who drive demand for goods and services and are ultimately responsible for the emissions. Production-based accounting methods used by national governments typically ignore emissions embodied in trade. In some countries, such as Belgium and Norway, over 50% of emission are embodied in trade (Hertwich and Peters 2009), thus production-based accounting methods ignore the crucial role that consumption plays in the production of greenhouse gas emissions globally.

Community consumption-based GHG accounting methods typically do not consider the contribution of local businesses to GHG emissions since they are part of production systems supplying goods and services to consumers. It is becoming increasingly common practice, however, to account for complete supply chain emissions of enterprises using methods similar to household consumption (Huang, Weber, and Matthews 2009). Including life cycle emissions of households and businesses in community GHG inventories will lead to double counting, unless subtracted, since a portion of local consumption will be from local production. Combining households and business activities into a single approach is often referred to as urban metabolism, accounting for life cycle environmental impacts of all materials consumed within a community's borders (Kennedy, Pincetl, and Bunje 2011). A smart GHG decision-support tool developed for the California Air Resources Board (contract 09-359) uses the urban metabolism approach to identify GHG hotspots and the cost of mitigation measures for all California cities (Jones and Kammen 2012).

Ultimately what is needed is a transformation of systems of production and consumption (Tukker et al. 2010a). In 2009 a U.N. panel on Sustainable Resources Management was convened to determine "how different economic activities influence the uses of natural resources and generation of pollution" (*UNEP* 2010). The report identifies consumption as the primary driving force, with fossil fuels and agriculture generating the most impacts on natural systems; however, there is considerable variation by country and region. For example, agriculture is the largest source of GHG emissions in most developing countries, while transportation is the single largest source in the United States. These differences point to the importance of differentiated GHG mitigation policies in each country. Chapters 3 and 4 of this dissertation explore in detail the extent to which GHG emissions and mitigation opportunities vary by locations within the United States. The assumption is that "smart" information tools that consider local demographic, economic, climatic and infrastructure characteristics of communities may help prioritize GHG reduction policies and practices for diverse actors.

2.5. Urban and regional planning for climate mitigation

Roughly 80% of the U.S. population lives in metropolitan areas, and about fifty percent live in suburbs (Jones and Kammen 2014). Suburbanization of American housing has been blamed with a long list of negative social, economic and environmental impacts. Low densities have decreased social interactions among residents, led to congestion and accidents, and increased the cost of providing infrastructure services, while longer traveling distances and larger homes increase environmental impacts, notably the emission of greenhouse gases. Several different schools of urban planning have attempted to address American sprawl.

Smart Growth grew directly out of a reaction to the negative social and environmental impacts of suburban sprawl (Ewing and Anderson 2008). Smart Growth principles emphasize a wide range of strategies, including compact design, preservation of open spaces, mixed land uses, grid street layouts, public transit, charging public costs to new development and revitalization of existing neighborhoods, among others (Burchell, Listokin, and Galley 2000; Downs 2005; Ewing et al. 1998). In practice, Smart Growth is discussed far more than it is successfully implemented due to a large number of barriers, including shifting power from local to regional authorities, redistributing benefits and costs to local actors, aversion to multi-family or low-income housing, raising home prices, increased traffic, complex permitting, and limits to individual choice, among others (Downs 2005). An even stronger limitation, in terms of climate change, is effectively addressing the existing housing stock. Revitalization tends to focus on improving urban cores to increase livability and density of low income neighborhoods (Downs 2005), leading, in theory, to a virtuous cycle of increasing social, economic and environmental outcomes (Cervero 2005). Smart Growth has far fewer tools to deal with existing suburban sprawl, where 50% of the U.S. population currently lives, and where the majority of residential carbon footprints will continue to exist into the future.

Transit-oriented development (TOD), a subset of smart growth strategies, has similarly yet to have a significant impact on American urban development. TOD is understood as high- or medium-density mixed use development located within walking distance of a major transit stop. TOD tends to focus on development around urban rail systems. A California study found that residents living near rail systems were five times as likely to commute by rail than average resident workers in the same city (Lund, Cervero, and Wilson 2004). While urban rail systems tend to support transit usage, their impact is still quite small on the urban landscape, with only roughly 5% of the U.S. workforce commuting by any public transit mode (Santos et al. 2011).

New Urbanism emerged in the early 1990s specifically to improve the social, economic and environmental outcomes of suburban development through integration of design elements common to traditional towns. Major design elements include a mix of residential and commercial spaces, highly walkable streets and integration of public transit systems (Fulton 1996). Architecture and street designs encourage social interactions, with front porches, garages behind homes, narrower streets and shared public spaces (Wheeler 2013). In contrast to smart growth, which emphasizes compact development and limiting suburbanization, New Urbanism tries to improve suburban development rather than restrict it. This is a promising development, and consistent with a place-based solutions approach, but it is also restricted in its ability to effectively deal with existing low density, car-dependent residential neighborhoods.

Another neighborhood-based design principle gaining momentum is zero net energy buildings (ZNEB) and developments. A ZNEB, or simply ZEB, is a residential or commercial building that meets its energy requirement with renewable energy. There are a number of competing definitions of net zero energy buildings (Pless and Torcellini 2010). Common to these definitions is the ability of buildings to be connected to the grid in order to use the grid as storage of on-site renewable energy. This has been shown to be environmentally beneficial compared to disconnected homes that produce and store all energy on site (Hernandez and Kenny 2010). In California, ZEBs have limited impact since household electricity and natural gas account for only roughly 10% of total household carbon footprints (Jones and Kammen 2014). When considering the full life cycle carbon footprints of residents, zero net energy communities are an improvement, but fall far short of meeting per capita climate stabilizations requirements. The widely discussed Beddington Zero Energy Development (BedZED) in the UK, for example, has been shown to have a lower carbon footprint than typical UK developments, but still requires 11 tCO_2e/yr per capita, or almost three times the global average, and nearly ten times what is required for climate stabilization, considered on a life cycle basis (Chance 2009).

Urban planning certainly plays an important role in greenhouse gas management. It is arguably the lack of effective urban and regional planning that has led to increasing consumption and GHG emissions in the United States over the last half-century. At the same time, there are countless examples of effective application of smart growth principles, climate action plan implementation and policy development to change local and regional drivers of GHG emissions (R. H. Ewing and Anderson 2008). If smart growth planning principles are to be more broadly applied it may be useful to consider under what conditions those principles are more or less effective. There appears to be a tendency for planning to rely on universal design principles that may not be appropriate for all locations. For example, while high-density urban cores clearly have lower GHG emissions than low-density suburbs (Cervero and Murakami 2010; Ewing and Cervero 2001a) this does not mean that marginal changes at low densities (i.e., putting more homes in distant locations) will produce a net reduction in emissions. Ultimately we need to transform household consumption in the existing housing stock if we are to address climate change at an appropriate scale, with planning and community-scale GHG management playing important roles.

2.6. The promise of place-based greenhouse gas management

Addressing climate change at sufficient scale will require massive adoption of low carbon technologies and practices in the coming decades. A large part of this transition must come from centralized planning, including market and regulatory approaches to limit emissions from power plants, motor vehicles, industry and agriculture, as well as increasing energy efficiency of buildings and end-use appliances. However, even if fully implemented at the national scale (which will almost certainly not happen), there is still a need for “bottom-up” or “multi-level governance” (Betsill and Bulkeley 2006) to speed up the adoption of low-carbon solutions. Urban planning and behavioral approaches have the potential advantage of achieving results more quickly than centralized policy measure that often take decades to reach their full effect.

Information deficit is one of the most commonly cited market failures preventing wider adoption of energy efficiency (Brown 2001; Golove and Eto 1996; Sutherland 1991). Smart planning tools that quickly identify cost-saving measures for households, businesses and local governments could reduce information barriers and transaction costs associated with acquiring such information. In practice though, information on pecuniary information has been shown to increase consumption of energy rather than decrease it (Delmas, Fischlein, and Asensio 2013).

At the same time, particular types of information tend to increase efficiency. For example, comparative feedback and tailored energy audits were shown to achieve substantial savings (11.5% and 13.5% respectively) in the same study.

Smart planning tools have the potential to scale up information-based social marketing efforts to large audiences. The approaches in this dissertation provide tailored, comparative feedback for households and communities in any U.S. location, a ranked list of GHG mitigation strategies and an inter-community GHG reduction competition that holds potential to scale up climate action within and between California communities. This research also seeks to aid in long-term, cross-jurisdictional planning efforts, that lead to broad cultural, as well as technological change, as advocated by Wheeler (2013, 2012, 2008) and others. Information that is tailored to each location can help planners choose from among a wide range of policy, planning and behavioral strategies that consider local population characteristics.

The next two chapters develop methods to quantify greenhouse gas profiles and reduction opportunities for U.S. households and communities. The results of this research are the foundation of online decision-support tools developed in collaboration with this research. Information tools alone may be necessary, but are far insufficient to enable large-scale change. Individuals also need to have sufficient motivation, capacity and self-efficacy, i.e., belief in their ability to make a meaningful contribution to solve the problem (Bandura 1977; Jackson 2004; McKenzie-Mohr and Schultz 2014). Chapters 5 explores these themes in more detail and Chapter 6 develops a pilot program to scale up meaningful climate action among California residents.

Chapter 3: Quantifying Carbon Footprint Reduction Opportunities of U.S. Households and Communities[1]

3.1. Introduction

Voluntary greenhouse gas (GHG) management programs and policies directed at individuals, households, and communities serve as compliments to national and state-level policies directed at heavy industrial emitters (Peters 2008; Ramaswami et al. 2008). Recently there has been a marked increase in information campaigns promoting lower-carbon lifestyles choices, community-based social marketing programs (McKenzie-Mohr 2013), voluntary carbon offsets programs (Anja Kollmuss, Zink, and Polycarp 2008), and the proliferation of online household carbon footprint calculators (Kim and Neff 2009) aimed at reducing emissions related to individual lifestyles. Several recent studies suggest that voluntary consumer-oriented programs can reduce household carbon footprints by 5-20% (Dietz et al. 2009; Laitner and Ehrhardt-Martinez 2009; Vandenbergh, Barkenbus, and Gilligan 2008). However, individuals and program developers need information on the relative contribution of different household activities to household carbon footprints as well as and the financial and GHG benefits of different household mitigation strategies.

In the United States, GHG emissions associated with household consumption have been estimated to account for over 80% of total U.S. emissions and upward of 120% if emissions embodied in imports are adjusted for the carbon-intensity of production (Hertwich and Peters 2009; Weber and Matthews 2008). An increasing number of studies have further analyzed the size, composition, and the demographic or geographic distribution of household carbon footprints at global, national, and regional scales (Hertwich 2005; Tukker et al. 2010b; Wiedmann 2009). While modeling techniques have become increasingly sophisticated, this research has not been translated into comprehensive carbon management tools available to households, communities, and small businesses to monitor and quantify emission reduction opportunities. Instead, relevant information available to individuals has been quite general in nature, such as providing lists of tips to reduce carbon footprints, or so-called carbon footprint calculators that only consider a limited portion of total household carbon footprints (Matthews, Hendrickson, and Weber 2008).

This chapter presents a consumption-based accounting model of U.S. household consumption, including GHG emissions released during the extraction, processing, transport, use and disposal phases of household transportation, energy, water, waste, food, goods, and services. Consumption-based accounting provides a comprehensive assessment of emissions related to individual consumer choices (Weber and Matthews 2008) and is well suited for the development of consumer-oriented carbon management tools (Wier et al. 2001). Carbon footprints are calculated for households in 28 cities across 6 household sizes and 12 income brackets for a total

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of over 2000 different household types. Greenhouse gas and financial savings are further quantified for a set of 13 potential mitigation actions across all household types. By applying the same basket of interventions across households with very different carbon profiles we demonstrate the utility of targeting policies and programs to specific geographic and demographic population segments. The results of this model have been incorporated into open access online carbon footprint management tools designed to enable behavior change at the household level in California ("Cool California" n.d.) and across the United States ("CoolClimate Network" n.d.) by providing personalized feedback to users on their carbon footprints.

3.2. Methods

The total household carbon footprint, HCF, of any individual or population can be expressed simply as the product of consumption, C, in dollars or physical units, and emissions per unit of consumption, E, summed over each emissions activity (i) included in the model:

$$HCF = \sum C_i E_i \quad (1)$$

Total annual household consumption, C, for each household type by location, household size, and income is calculated as:

$$C = \sum \left[C_{msa,\,i} \ * \ C_{t,i} / C_{usa,i} \right] \quad (2)$$

where $C_{msa,i}$ is the average household consumption, in dollars, in each metropolitan statistical area (msa) in the Consumer Expenditures Survey (CEX) (Bureau of Labor Statistics 2008) of each expenditures category (i), $C_{t,I}$ is the average household expenditures by each household type (t, by size and income) in the CEX, and $C_{usa,i}$ is the average U.S. household consumption, in dollars or physical units. Average U.S. default consumption values, $C_{usa,i}$, for the year 2005 are from the Bureau of Transportation Statistics (Bureau of Transportation Statistics 2002) for transportation (in vehicle miles and passenger miles for public transit modes), the Energy Information Agency (U.S. Energy Information Administration 2014a) for household energy (in physical energy units) at the level of U.S. states, and the Bureau of Economic Analysis (Bureau of Economic Analysis 2002b) (BEA) for food, goods, and services. BEA expenditures on 589 unique products were then matched with 8 categories of food, 7 categories of goods, and 10 categories of services in the CEX. A detailed version of the CEX (with ~1500 categories in total) was obtained from the Bureau of Labor Statistics (2006) in order to separate goods from services where these categories were combined in the CEX summary tables.

In eq 2 above, the CEX is used to scale average consumption in each major metropolitan statistical region by average consumption of each household type, by size and income, compared to U.S. average consumption. Location, income, and household size have been reported elsewhere to be the largest determining factors of household environmental impacts (Lenzen 1998; Wier et al. 2001). The total number of households in the United States in 2005 was roughly 118M, with 2.5 persons per household, on average. Expenditures for income brackets between $70,000 and $120,000 were interpolated linearly. Expenditures for cities are for the combined year 2005-2006 for 17 of the 28 cities, and for the next earliest year date are available in the CEX for other cities, adjusted to 2005 USD using the Consumer Price Index. The model uses state average electricity and home heating fuel consumption and prices (Bureau of Labor Statistics 2006). Correction factors are applied to account for price differences of food, goods, and services in each MSA using the ACCRA Cost of Living Index (C2ER 2014).

3.2.1. Detailed methods of benchmark carbon footprint model

3.2.1.1. Motor Vehicles

Emissions from motor vehicles include: 1) direct tailpipe emissions from fuel combustion in vehicles, 2) indirect "well-to-pump" emissions from the pre-consumer life cycle of fuels, 3) vehicle manufacturing, and 4) vehicle maintenance and repairs (including parts and services). Government-related indirect emissions from road construction and maintenance, policing, and other activities are currently not included in the model.

Direct tailpipe emissions

The average U.S. household drove 21,200 vehicle miles in 2001 (Bureau of Transportation Statistics 2002), the latest year national average household vehicles miles traveled are available at the time of model construction. The weighted fuel economy of the U.S. vehicle fleet is about 20 miles per gallon (Davis, Diegel, and Boundy 2003). Combustion of a gallon of gasoline produces 8,874 gCO_2 and diesel produces 10,153 gCO_2 (Energy Information Administration 2014). For benchmarking purposes, all vehicles are initially assumed to be gasoline since diesel vehicles account for only a small fraction of the U.S. vehicle fleet, although users of the online tool (CoolClimate Network 2014) can further specify gasoline or diesel fuel type. Other vehicle fuels (e.g., biofuels and electricity) are currently not included in the model. Direct emissions for the average U.S. household (with 2.5 persons) are calculated as: 21,200 miles / 20 mpg * 8,874 gCO_2/gallon = 11.9 mtCO2e/yr.

The calculator populates default values for the average number of vehicles and average miles per vehicle for each household type (using equation 2). The default number of vehicles per household is given by the Consumer Expenditures Survey (Bureau of Labor Statistics 2006) and is rounded to the nearest whole number. Vehicle miles traveled are distributed per vehicle using the National Household Travel Survey (Bureau of Transportation Statistics 2002):

Table 1. Allocation of vehicle miles per number of vehicles owned by households

% miles per year per number of vehicles			
	# of vehicles in household		
	1	2	3
first vehicle	100%	55%	41%
second vehicle	0%	45%	35%
third vehicle	0%	0%	24%

source: NHTS, 2006

Indirect "well-to-pump" emissions

Estimating emissions from the full life cycle of transportation fuels (from "well-to-wheels") has become increasingly important aspect of transportation policy. In order to compare emissions from disparate transportation energy sources, such as biofuels, natural gas and electricity, a life cycle assessment (LCA) approach is required. California's "Low Carbon Fuel Standard" (LCFS) mandates life cycle accounting in an effort to increase the use low carbon transportation fuels in the State. The LCFS policy analysis report of 2007 (Farrell and Sperling 2007) identifies 20% as a typical value of well-to-pump emissions for gasoline, citing the GREET (Environmental Protection Agency 2013) model in its technical report (Farrell and Sperling 2007). Well-to-pump (WTP) gasoline emissions in GREET are 26% of tailpipe emissions (or roughly 20% of well-to-wheel emissions), while diesel WTP emissions are 23% of direct emissions. Delucci's (2006) estimate of 20,778 gCO_2e/106 btu for pre-combustion gasoline emissions equates to 29% of direct emissions. EIO-LCA (Green Design Institute, C.M.U. n.d.) produces a more conservative estimate of about 14%. Horvath (Horvath 2006) and other studies have previously assumed a value closer to this lower estimate (Granovskii, Dincer, and Rosen 2006; Spielmann and Scholz 2005). The LCFS program in California is currently developing default well-to-wheels emission factors for transportation fuels, and a similar effort has been proposed at the national level. Until standard default values are determined by state or national policy directives, we have chosen the GREET model as the most representative emission factors for well-to-pump emissions.

Vehicle manufacturing

EIO-LCA is used to approximate emissions from motor vehicle manufacturing. The average retail price of a domestic automobile was $17,907 (Davis, Diegel, and Boundy 2003) in 1997. The average producer price was 80% of the retail price (Bureau of Economic Analysis 2002b), or $14,326. Applying the 1997 EIO-LCA emission factor of 628 gCO_2e/$ for the "Automobile and light truck manufacturing sector" in EIO-LCA results in 9.0 $mtCO_2e$ per vehicle. This estimate is consistent with process-based LCA studies, which include the most significant emissions from vehicle manufacturing, but exclude economy-wide impacts further up the supply chain. Published studies include estimates of 4.4 $mtCO_2e$ for a Volkswagen Golf (Schweimer and Levin 2000), 8-9 $mtCO_2e$ for Ford Galaxy and S-Max models (Schmidt 2006), 9-10 $mtCO_2e$ for Mercedes S Class models (Finkbeiner and Hoffmann 2006) and 6.8 $mtCO_2e$ from vehicle components and assembly over the lifetime of a typical vehicle in the GREET (Environmental Protection Agency 2013) model.

Allocating emissions from motor vehicles, as with other consumer goods with long life spans, presents challenges to carbon footprint calculator designers. Should upstream emissions from the production of vehicles be allocated at the time of purchase, or over the lifetime of the vehicle? When a vehicle is sold, what portion of manufacturing emissions should be allocated to the new owner? Allocating emissions at the time of purchase produces a disincentive to purchase new, and potentially more fuel-efficient vehicles. If, on the other hand, emissions are allocated over the lifetime of vehicles on a per-mile-basis, there is no incentive to reduce the very significant emissions from vehicle manufacturing.

Table 2 provides an example of the effect of different assumptions for embodied motor vehicle emissions. Increasing fuel efficiency from 25 to 40 mpg for a vehicle driven 10,000/yr reduces well-to-wheel GHG emissions by ~1.6 mtCO_2e/yr (1.3 direct plus 0.3 well-to-pump) or 16 mtCO_2e over 10 years. If 9 mtCO_2e of manufacturing emissions are allocated at the time new vehicles are purchased, then it would take nearly 6 years for this action to result net GHG savings. Purchasing a new fuel-efficient vehicle every 3 years would result in net negative savings (additional emissions) of 11 mtCO_2e over 10 years with no manufacturing emissions passed on to the future owners of these vehicles. If, on the other hand, embodied emissions are allocated on a per mile basis, then driving a 40 mpg vehicle would result in lifecycle savings of 10 mtCO_2e over 10 years, regardless of how many new or used vehicles are purchased over this period. Thus, from one perspective regularly purchasing new fuel-efficient vehicles reduces net GHG emissions, while from the other perspective net emissions are increased.

Table 2. Allocating vehicle manufacturing emissions at time of purchase or on a per mile basis

Effect of purchasing more efficient vehicle under different embodied GHG emissions assumptions (switching from a 25 mpg to 40 mpg vehicle, driving 100,000 miles in 10 years)

Allocation of manufacturing GHG emissions	Frequency new or used vehicles purchased	mtCO2e saved in fuel consumption	mtCO2e from vehicle manufacturing	Net CO2e saved
Allocated upfront	New every 3 yrs	16	27	-11
Allocated upfront	New every 5 yrs	16	18	-2
Allocated upfront	New every 10 yrs	16	9	7
Allocated upfront	Used every 3 yrs	16	0	16
Allocated upfront	Used every 5 yrs	16	0	16
Allocated upfront	Used every 10 yrs	16	0	16
Allocated per mile	New every 3 yrs	16	6	10
Allocated per mile	New every 5 yrs	16	6	10
Allocated per mile	New every 10 yrs	16	6	10
Allocated per mile	Used every 3 yrs	16	6	10
Allocated per mile	Used every 5 yrs	16	6	10
Allocated per mile	Used every 10 yrs	16	6	10

Assumptions:
Direct emissions = 8874 gCO2/gallon
Well-to-pump emissions = 20% of direct emissions
Manufacturing emissions = 9 mtCO2e/vehicle
Vehicle lifetime = 160,000 miles

Another, seemingly more reasonable, approach would be to allocate emissions based on depreciation of vehicles on an annual basis. This would allocate most of the emissions to the early years of a vehicle's lifetime and fewer emissions toward the end; however, such an allocation process is difficult to accomplish in practice and has not been included in the current model.

For the current calculator we chose to allocate emissions from vehicle manufacturing on a per mile basis for the following reasons: 1) the preferred method of allocation based on vehicle deprecation was not feasible, 2) allocating emissions on a per mile basis sends a signal to reduce vehicle miles traveled, which is arguably more important than limiting production of motor vehicles, and, 3) encouraging the purchase of more fuel efficient vehicles stimulates innovation, which can lead to future emission reductions.

Emissions per vehicle mile are calculated as:

$$\frac{9tCO2e}{vehicle} * \frac{vehicle}{160{,}000miles} = \frac{56kgCO2e}{mile}$$

where 160,000 miles is the average expected lifetime of motor vehicles (Environmental Protection Agency 2013).

Vehicle maintenance and repairs
EIO-LCA is used to approximate emissions from motor vehicle maintenance and repairs. See Food, Goods and Services discussion below.

3.2.1.2. Public Transportation

The expense "Public transportation" in the Consumer Expenditures Survey aggregates air travel, bus, rail, and other into a single expenditures category, complicating the use of CEX for benchmarking purposes for different transport modes. Emissions from public transport were determined by 1) converting dollars to passenger miles using a top-down approach, 2) allocating miles to different transport modes, 3) multiplying passenger miles by GHG emission factors for each mode, 4) scaling emissions based on income, 5) accounting for the higher fraction of air travel miles for households at higher incomes.

The Transportation Energy Data Book provides total U.S. passenger miles per transport mode (Table 3). The vast majority of passenger miles for non-highway vehicles are for air transportation (93%), followed by 3% from Bus, 3% from transit and commuter rail, and 1% for long distance rail (Amtrak).

Table 3. Passenger miles per public transportation mode (2004)

Mode	Total US (millions)	Per capita	%
Air*	752,341	2,566	93%
Bus	21,262	73	3%
Transit (light&heavy)	15,930	54	2%
Communter rail	9,719	33	1%
Amtrak	5,511	19	1%
Total		2,745	100%

Source: Transportation Energy Data Book, 2007

* includes domestic and international flights

According to the Transportation Energy Data Book (Davis, Diegel, and Boundy 2003) thirty-one percent of all long-distance trips are for business. These emissions are theoretically embodied in goods and services so are not included under here. Total average public transportation miles (including air travel) are defined as:

$$\frac{2745 miles*}{person} * 69\% * \frac{2.5 persons}{household} = \frac{4735 miles}{household}$$

The average US household spent $505 per year on public transportation in 2006, or 9.4 miles per dollar. We multiply consumer expenditures by 9.4 and scale total passenger miles for each income level and household size.

To calculate benchmark transportation miles for each household type we then calculated the fraction of total passenger miles by each major mode of transport using the Transportation Energy Data Book, 2007 (Davis, Diegel, and Boundy 2008). Air travel accounted for 93% of total passenger miles for all major public transport modes in 2004. Air travel is a normal good; as income goes up, so do expenditures on air travel, i.e., showing a positive income elasticity of demand. Other public transport modes are inferior goods, with lower demand as income increases over middle incomes. Households earning less than $25k per year take more trips by bus than by air, while household earning more than $75k per year take nearly 10 times the number of long distance trips by air than by bus (Table 4).

Table 4. Percent of long distance trips by mode and income

	Less than $25K		$25K-$49K		$50-$74K		$75K+	
Mode	**%**	**$**	**%**	**$**	**%**	**$**	**%**	**$**
Air	38%	$ 77	58%	$ 161	63%	$ 347	85%	$ 846
Bus	49%	$ 97	32%	$ 89	24%	$ 131	9%	$ 93
Train	9%	$ 18	9%	$ 25	10%	$ 52	5%	$ 49
Other	4%	$ 8	2%	$ 4	4%	$ 20	1%	$ 12
Total	100%	$ 200	100%	$ 280	100%	$ 550	100%	$ 1,000

% source: BTS, 2006. Americans on the go. Table 13.

Total $ source: Consumer Expenditures Survey, 2006

$ per mode is interpolated

The final calculation for public transportation is:

$$\frac{\$}{year} * \frac{9.4miles}{\$} * \frac{miles_{mode}}{miles_{total}} * \frac{CO2e}{mile_{mode}}$$

Emission factors for public transit modes are from the Greenhouse Gas Protocol (Ranganathan et al. 2004) which incorporates studies by EPA and other sources (Table 5). These estimates assume average occupancy of public transit modes.

Table 5. Emission factors for public transit modes

Mode	gCO2e/mile
bus	300
commuter rail (light & heavy)	165
transit rail (subway, tram)	160
Amtrak	191

Source: Greenhouse Gas Protocol (WRI-WBCSD)

Indirect well-to-pump emissions from transportation fuels are assumed to be 26% of direct emissions, as indicated by the GREET model (Environmental Protection Agency 2013).

3.2.1.3. Air Travel

Air travel results in 1) direct CO_2 emissions from fuel combustion, 2) indirect life cycle ("well-to-pump") GHG emissions from fuel processing and other indirect emissions from the airline industry, and 3) non-CO_2 atmospheric effects on global and local temperatures and weather patterns.

GHG emissions from consumption have been shown to vary substantially depending on aircraft type, flight distance, number of stops, seat occupancy rate and seat class (Kollmuss and Lane 2008). Few online calculators, however, present this level of customization, presumably due to the additional modeling efforts required and the preference to build simple, user-friendly interfaces that require less time to complete. DEFRA (2008) is commonly cited as a reference for GHG emission factors. This report considers typical flights within the U.K., within the E.U. and transatlantic flights. Trip length and emission factors, converted to miles and gCO_2 per passenger mile, are:

Trip length	gCO2/passenger-mile
288 miles	254
688 miles	210
4027 miles	170

Shorter flights have higher emission factors due to relatively higher emissions at takeoff and landing per passenger-mile. Extrapolating these numbers using a logarithmic curve, and assuming typical trip length of ~1200 miles (Department of Transportation 2014a), yields the following emissions estimates per given trip length:

Trip length	gCO2/passenger-mile
Number of short flights (<400 mi)	254
Number of medium flights (400-1500)	204
Number of long flights (1500-3000)	181
Number of extended flights (>3000)	172
Typical flight (1200)	200

Indirect "well-to-pump" emissions are assumed to be 26% of direct emissions, following the GREET model (Environmental Protection Agency 2013). Other indirect emissions, e.g., from the airline industry, are excluded from this analysis.

Airplanes traveling at high altitude have large, varied and relatively uncertain effects on surface temperature. These impacts include warming from 0_3, H_20, soot, contrails and cirrus clouds, and cooling effects from breakdown of CH_4 and emissions of sulfates and aerosols. The average net result on global radiative forcing -not including the large but uncertain effects from cirrus clouds- is reported to be roughly equivalent to the warming effect of direct CO_2 emissions from fuel consumption (Sausen et al. 2005). However, simply multiplying CO_2 emissions by a factor to account for radiative forcing can lead to false conclusions (Kollmuss and Crimmins 2009). The climate impact of individual flights varies considerably, ranging from net cooling in some cases to flights with several times the impact of typical flights. The particular contribution of warming and cooling factors depends on altitude, temperature, humidity, the chemical composition of air, geographic region, time of day, season and other factors. Impacts also occur over vastly different time scales, ranging from hours to centuries, thus complicating the selection of global warming potential of a single pulse of emissions. Furthermore, net radiative forcing models assume that warming in one location cancels cooling in another, rather than producing separate distinguishable impacts on local climates.

Despite the limitations of using radiative forcing, carbon calculator modelers need some way to express climate impacts from air travel without relying on highly complex models with detailed and time-consuming user interfaces. In the absence of standards, carbon footprint calculator modelers have typically chosen to either ignore non-CO_2 impacts, or include a factor to account for radiative forcing. In the current version of the calculator we use the radiative forcing multiplier of 1.9 as proposed by Sausen et al. (2005) to account for non-CO_2 impacts. While this factor is not specific to individual flights is it is a reasonable representation of average climate impacts from air travel. This approach is consistent with the assumption of typical impacts from consumption in the rest of the calculator. The total multiplier to account for for non-CO_2 atmospheric effects and well-to-pump emissions (1.9 + 0.26) is rounded to 2, i.e., total air travel emissions = direct emissions x 2. This is very likely a conservative number considering we have not included the large but uncertain global warming impact of cirrus cloud formation or emission from airports.

3.2.1.4. Household Energy

Household consumption of electricity, natural gas and other fuels is provided in dollars by the CEX for each household type by income and size. However, CEX does not disaggregate electricity, natural gas and other fuels for metropolitan statistical areas. Regional energy consumption varies considerably due to different energy prices, weather, heating fuels, housing size and construction and other factors (Glaeser and Kahn 2010). Another possible source of data, the American Housing Survey (AHS) (U.S. Census 2014a), provides average expenditures on electricity, natural gas and other fuels for each city; however, the AHS only includes a sample of cities every two years and inter-annual variation of energy consumption would confound comparisons. A modeling approach may be best suited to account for both regional variation and the influence of household types on energy consumption; however, such an approach is outside the scope of the current study.

Given the data limitations mentioned above, we have approximated benchmark electricity and natural gas consumption for each household type (location, household size and income) as follows:

$$I = D_h * P_s * E_s$$

where,
I = impact, expressed in gCO_2e/year
D = dollars spent per year on electricity or natural gas for each household type (h) of income and household size in the CEX
P = price of energy per US State (s) in dollars per physical unit of fuel
E = emission factor for each US State (s) in gCO_2e per physical unit of fuel

This formula effectively scales state-level consumption of electricity, natural gas and other fuels by household type (size and income) for the default values in the calculator. As in all other section of the calculator, users can overwrite the default values with their own consumption levels (in dollars or physical units). A discussion of emission factors used in the analysis follows.

Direct emissions from household energy

Households contribute direct GHG emissions from the burning of fossil fuels in homes. Natural gas is typically the largest single contributor to direct household emissions for U.S. households. Natural gas is assumed to produce 117 lbs CO_2/Mbtu. The CEX category “fuel oil and other fuels” includes expenditures on fuel oil, coal, wood, bottled gas and other fuels, accounting for 8% of total household energy expenditures for the average U.S. household, and 0.3% of total household expenditures. Published CEX tables do not disaggregate consumption by individual fuels, making approximation difficult. Considering the relatively small contribution to total household GHG emissions from other fuels for most households, we use a single emission factors of 682 gCO_2e/$ provided by the EIO-LCA (Green Design Institute, C.M.U. n.d.) model. This approximation can be expected to contribute only a very small fraction of the total uncertainty in carbon footprint estimates for most households, although in northeastern United States, where heating oil is more predominant, the total uncertainty can be expected to be substantially higher. Further work will be required to refine this calculation in future versions of the calculator, which may provide more reasonable estimates based on fuel consumption of different fuel types in physical units.

Other direct emissions from wood burning, fertilizers, and chemical processes are assumed to be relatively small in comparison to other categories of emissions and are excluded from the current analysis.

Indirect emissions from electricity production

Greenhouse gas emission factors (EF) for electricity are from eGRID (U.S. E.P.A. 2013). This database aggregates air emissions for each generator at thousands of electricity power plants in the United States. Aggregation is available at the level of U.S. states and 25 grid sub-regions. The eGRID data provided at the level of U.S. states account for generated electricity only, excluding imports and exports of electricity, and are therefore are not appropriate for the development of carbon footprint calculators. EPA recommends the use of eGRID sub-regions for accounting purposes; however, sub-regions do not always correspond well with U.S. states, which is currently the only geographic information asked by users in our online model. As a partial solution to this problem, we map the boundaries of U.S. states to individual eGRID subregions, with the exception of New York, which is assumed to be the average of three subregions.[2] In the case of California, users can select electric utility provider, with GHG emission factors for the year 2006 provided by the California Air Resources Board (ARB 2010), as reported to the California Climate Action Registry.

Indirect emissions from electricity and natural gas life cycles

Electricity consumption also indirectly results in GHG emissions during the production, processing, transmission and storage of fuel, as well as during the construction and maintenance of power plants. Pacca and Horvath (2002) first approximated pre-combustion and construction life cycle emissions from coal, natural gas, wind, hydro and solar power plants in the Upper Colorado River Basin. Total life cycle emissions were 9% higher than emissions from combustion alone for a coal-fired power plant and 14% higher for a natural gas plant. Using a different methodology, Jaramillo et al (2007) produced roughly the same results for these fuel sources. We developed pre-combustion indirect electricity emission factors for each eGRID subregion by multiplying the fuel mix in each region by emission factors (tCO2e/MWh) provided by Pacca and Horvath. When state boundaries include more than one eGRID subregion we used the average fuel mix for those regions. The results are shown in Table 6. For the average U.S. fuel mix, pre-combustion emissions are 9% of combustion emissions. With the exception of Alaska, which is dominated by hydro power, indirect emissions are between 8%-12% of direct emissions. Considering the margin of error in this analysis is likely greater than the difference between indirect emission factors for U.S. states, the current online model applies the U.S.

[2] We are currently conducting research to offer more geographically-specific electricity emission factors in future versions of the calculator, but this work was not completed at the time of this writing.

average indirect factor for all U.S. states. Future online versions of the calculator may incorporate the state-specific factors.

We assume indirect emissions from natural gas (including extraction, processing and piping natural gas to homes) add 14% to direct emissions per Jaramillo et al. (2007).

Table 6. tCO2 per 5.55 MWh/yr capacity of electric generation per U.S. state and eGRID subregion

		Direct*			Indirect**						Indirect
State (eGRID subregion)	%***	Coal	Gas	Total	Coal	Gas	Wind	Hydro	Solar	Total	/ Direct
USA	78%	37.85	8.92	46.77	3.11	1.23	0.02	0.03	-	4	9%
Alabama (SRSO)	0.79	50.51	4.53	55.04	4.15	0.62	-	0.02	-	5	9%
Alaska (AKMS)	0.70	-	1.53	1.53	-	0.21	0.00	0.34	-	1	36%
Arizona (AZNM)	0.81	35.70	13.06	48.76	2.93	1.80	0.00	0.02	0.00	5	10%
Arkansas (SRMV)	0.68	16.54	18.66	35.20	1.36	2.58	-	0.01	-	4	11%
California (CAMX)	0.74	9.29	17.46	26.75	0.76	2.41	0.02	0.09	0.03	3	12%
Colorado (RMPA)	1.00	55.94	8.04	63.98	4.59	1.11	0.01	0.04	-	6	9%
Connecticut (NEWE)	0.58	11.82	15.14	26.96	0.97	2.09	0.00	0.03	-	3	11%
Delaware (RFCE)	0.56	35.19	3.98	39.17	2.89	0.55	0.00	0.00	-	3	9%
District of Columbia (SRVC)	0.57	39.38	2.04	41.42	3.23	0.28	-	0.01	-	4	9%
Florida (FRCC)	0.65	20.48	16.12	36.60	1.68	2.23	-	0.00	-	4	11%
Georgia (SRSO)	0.79	50.51	4.53	55.04	4.15	0.62	-	0.02	-	5	9%
Hawaii (HIMS)	0.05	1.15	-	1.15	0.09	-	0.00	0.02	-	0	10%
Idaho (NWPP)	0.95	26.81	4.48	31.29	2.20	0.62	0.01	0.25	-	3	10%
Illinois (RFCW)	0.76	56.83	1.13	57.96	4.67	0.16	0.00	0.00	-	5	8%
Indiana (RFCW)	0.76	56.83	1.13	57.96	4.67	0.16	0.00	0.00	-	5	8%
Iowa (MROW)	0.84	57.37	1.67	59.04	4.71	0.23	0.02	0.02	-	5	8%
Kansas (SPNO)	0.85	61.07	2.45	63.52	5.02	0.34	0.01	0.00	-	5	8%
Kentucky (SRTV)	0.78	52.08	1.48	53.56	4.28	0.20	-	0.04	-	5	8%
Louisiana (SRMV)	0.88	64.89	1.45	66.34	5.33	0.20	-	0.01	-	6	8%
Maine (NEWE)	0.58	11.82	15.14	26.96	0.97	2.09	0.00	0.03	-	3	11%
Maryland (RFCE)	0.56	35.19	3.98	39.17	2.89	0.55	-	0.00	-	3	9%
Massachusetts (NEWE)	0.58	11.82	15.14	26.96	0.97	2.09	0.00	0.03	-	3	11%
Michigan (RFCM)	0.81	52.20	5.68	57.88	4.29	0.78	-	-	-	5	9%
Minnesota (MROW)	0.84	57.37	1.67	59.04	4.71	0.23	0.02	0.02	-	5	8%
Mississippi (SRSO)	0.79	50.51	4.53	55.04	4.15	0.62	-	0.02	-	5	9%
Missouri (SRMW)	0.88	64.89	1.45	66.34	5.33	0.20	-	0.01	-	6	8%
Montana (NWPP)	0.95	26.81	4.48	31.29	2.20	0.62	0.01	0.25	-	3	10%
Nebraska (MROW)	0.84	57.37	1.67	59.04	4.71	0.23	0.02	0.02	-	5	8%
Nevada (NWPP)	0.95	26.81	4.48	31.29	2.20	0.62	0.01	0.25	-	3	10%
New Hampshire (NEWE)	0.58	11.82	15.14	26.96	0.97	2.09	0.00	0.03	-	3	11%
New Jersey (RFCE)	0.56	35.19	3.98	39.17	2.89	0.55	0.00	0.00	-	3	9%
New Mexico (AZNM)	0.81	35.70	13.06	48.76	2.93	1.80	0.00	0.02	0.00	5	10%
New York (YNLI/NYCW/NYUP)	0.44	5.60	11.73	17.33	0.46	1.62	0.00	0.05	-	2	12%
North Carolina (SRVC)	0.57	39.38	2.04	41.42	3.23	0.28	-	0.01	-	4	9%
North Dakota (MROW)	0.84	57.37	1.67	59.04	4.71	0.23	0.02	0.02	-	5	8%
Ohio (RFCW)	0.76	56.83	1.13	57.96	4.67	0.16	0.00	0.00	-	5	8%
Oklahoma (SPSO)	0.98	43.44	15.45	58.90	3.57	2.13	0.01	0.02	-	6	10%
Oregon (NWPP)	0.95	26.81	4.48	31.29	2.20	0.62	0.01	0.25	-	3	10%
Pennsylvania (RFCE)	0.56	35.19	3.98	39.17	2.89	0.55	0.00	0.00	-	3	9%
Rhode Island (NEWE)	0.58	11.82	15.14	26.96	0.97	2.09	0.00	0.03	-	3	11%
South Carolina (SRVC)	0.57	39.38	2.04	41.42	3.23	0.28	-	0.01	-	4	9%
South Dakota (MROW)	0.84	57.37	1.67	59.04	4.71	0.23	0.02	0.02	-	5	8%
Tennessee (SRTV)	0.78	52.08	1.48	53.56	4.28	0.20	-	0.04	-	5	8%
Texas (ERCT)	0.86	28.92	19.63	48.55	2.38	2.71	0.01	0.00	-	5	10%
Utah (NWPP)	0.95	26.81	4.48	31.29	2.20	0.62	0.01	0.25	-	3	10%
Vermont (NEWE)	0.58	11.82	15.14	26.96	0.97	2.09	0.00	0.03	-	3	11%
Virginia (SRVC)	0.57	39.38	2.04	41.42	3.23	0.28	-	0.01	-	4	9%
Washington (NWPP)	0.95	26.81	4.48	31.29	2.20	0.62	0.01	0.25	-	3	10%
West Virginia (RFCW)	0.76	56.83	1.13	57.96	4.67	0.16	0.00	0.00	-	5	8%
Wisconsin (MROE)	0.84	53.02	4.95	57.98	4.35	0.68	0.00	0.02	-	5	9%
Wyoming (NWPP)	0.95	26.81	4.48	31.29	2.20	0.62	0.01	0.25	-	3	10%

* Includes direct fuel combustion emissions from coal and natural gas power plants, as reported by Pacca and Horvath, 2002

** Includes indirect emissions from precombustion, steel, concrete and aluminum for hydro, wind and solar PV power plants, as reported by Pacca and Horvath, 2002

* *E* lectricity generation from coal, natural gas, hydro, wind and solar as a fraction of the total resources mix, as reported by eGRID. Resouces not included are nuclear, oil, geothermal, biomass, other fossil fuel and unknown sources

3.2.1.5. Water and waste

The category "Water and other public services" in the CEX includes: water and sewerage maintenance, trash and garbage collection and septic tank cleaning. Emission factors (CO_2e/$) for these services can be expected to vary widely from one location to the next. For example, according to the California Energy Commission (2007) water supply, conveyance, distribution and treatment requires 5,411 kWh per million gallons of indoor consumption in Northern California compared to 13,022 kWh per million gallons in Southern California.

Regionalized emissions data on water and waste across the United States are not currently available and collection of these data was beyond the scope of the current study. Although EIO-LCA is not capable of providing estimates of water and waste emissions at regional scales, it provides a reasonable rough proxy for average emissions at the national level. Since total emissions from water and waste amount to less than 3% of total emissions, this error can be considered minor, when weighed against the total household carbon footprint. Emissions from waste and waste are approximated by multiplying expenditures on "water and other public services" in the CEX by an emission factor of 4121 gCO_2e/$ provided by EIO-LCA (Green Design Institute, C.M.U. n.d.) for the sector "water and remediation services".

3.2.1.6. Shelter

Few life cycle assessment studies of housing construction in the United States are currently available. This is rather surprising given the recent emphasis on "green building" practices for home construction. Results from case studies vary widely, including estimates of 20 $mtCO_2e$ for construction of a home in Canada (Baouendi, Zmeureanu, and Bradley 2005), 21 and 37 $mtCO_2$ for wood frame homes built in Atlanta and Minneapolis, respectively (Lippke et al. 2004), and 80 $mtCO_2$ for two homes in Michigan (Blanchard and Reppe 1998). It is unclear the extent to which differences are the result of methodological choices (e.g., the boundary of system analyzed) or actual differences in housing construction materials and processes. These few case studies may also not be representative of typical homes built in the United States.

Using the top-down economy-wide EIO-LCA approach, Ochoa et al. (2005) estimate total emissions from U.S. housing construction of new residential 1-unit structures at 110 million $mtCO_2e$ in 1997, which equates to 100 $mtCO_2e$ per home for the 1.1M single-unit homes completed in that year (U.S. Census 2014b). Amortizing these emissions over a 50 year expected life time for the average single-unit home built in 1997 of 2,150 square feet (U.S. Census 2014b) results in an annualized emission factor of 930 gCO_2e per square foot.

Ochoa et al. acknowledge the high level of uncertainty associated with the EIO-LCA approach for housing construction and some of this research team proposed a hybrid approach in a later paper (Bilec et al. 2006). In the absence of improved emission factors available for typical U.S. housing construction, we use the approximated EIO-LCA value of 930 gCO_2e per square foot. Further emissions from maintenance and repairs are accounted for under goods and services in the calculator under "Household maintenance and repair services" and "household furnishing and equipment".

The average square feet of homes is determined by income level, as provided by the 2005 American Housing Survey (U.S. Census 2014a) of the United States. When the user selects household size (one person, two person, etc.) the calculator displays average square footage of home (owned or rented) based on the average household income of a household of that size.

Table 7. Average U.S. home size (square feet) by income level

Income	sqft
Less than $10,000*	1420
$10,000 to $19,999*	1419
$20,000 tp $29,999*	1502
$30,000 to $39,999*	1591
$40,000 to $49,999	1689
$50,000 to $59,999	1750
$60,000 to $79,999	1854
$80,000 to $99,999	1993
$100,000 to $119,999	2217
$120,000 or more	2500

source: American Housing Survey, 2005
*average of two categories

3.2.1.7. Food, Goods and Services

We use the Economic Input-Output Life Cycle Assessment model (Green Design Institute, C.M.U. n.d.), EIO-LCA, designed by the Green Design Institute at Carnegie Mellon University, and the Comprehensive Environmental Database Archive (Suh 2005), CEDA4.0 to calculate emissions from food, goods and services. EIO-LCA and CEDA are widely used economy-wide models of cradle-to-gate emissions of all major greenhouse gases for >420 economic sectors of the U.S. economy, of which 289 sectors are applicable to consumer demand (the rest are intermediate goods). Since emission factors are provided per dollar of industry output, and not per dollar of consumer expenditure, only the fraction of consumer dollars that is received by manufacturing industries should be input into EIO-LCA to determine emissions from manufacturing (Hendrickson, Lave, and Matthews 2010). We further calculate separate emission factors for transport to market (truck, rail, air) and wholesale and retail trade by multiplying the fraction of consumer dollars received at each life cycle stage to the corresponding emission factor in EIO-LCA, similar to (Norris, Croce, and Jolliet 2002) and outlined in. In order to update these emission factors from 1997 benchmark year, we adjust for inflation using the Producer Price Index (PPI).

New EIO-LCA greenhouse gas emission factors for 2005 are therefore estimated as:

$$EF_{C,i} = \left(\frac{PV_i}{CV_i} * EF_{P,i} + \frac{Truck}{CV_i} * EF_{P,t} + \frac{Rail}{CV_i} * EF_{P,r} + \frac{Air}{CV_i} * EF_{P,a} + \frac{WT}{CV_i} * EF_{P,wt} + \frac{RT}{CV_i} * EF_{P,rt} \right) * PPI_i$$

where GHG emission factor (EF) is given in consumer dollars (C) or producer dollars (P) for each industry (i). PV represents the total value received by the producing industry (i) of dollars spent by consumers (CV) of commodities from industry (i). Truck, Rail and Air represent the value received by each sector to ship products to market, while wholesale trade (WT) and retail trade (RT) is the value-added from wholesale and retail trade (Bureau of Economic Analysis 1997). Emission factors (EF) for trucking (t), rail transport (r), air transport (a), wholesale trade (wt) and retail trade (rt) are in given in producer dollars in EIO-LCA. The sum of all factors produces total emissions per consumer dollar at the point of sale for each of 589 commodities or services in the BEA accounts (Bureau of Economic Analysis 2002a). PPI is the Producer Price Index for each (of 70) I-O sector (i).

Next, we created a concordance table between 589 products in BEA input-output accounts into 6 categories of food, 7 categories of goods, and 10 categories of services, consistent with the calculator and the CEX datasets. Emissions for each category of consumption in the calculator are an average of emissions for all individual products in that category, weighted by average national expenditures on those products. For example, although adhesives and glues have an unusually high emission factor, at more than 700 gCO_2e/consumer \$, they account for less than 2% of expenditures on office supplies. Therefore, the overall emission factor for office supplies is not greatly affected by the high emission factor of adhesives and glues. A list of final emission factors is provided in Table 8.

A note on uncertainty: While emission factors using input-output (I-O) analysis are generally robust on the aggregate, there are basic well-understood limitations of the approach. It is essential to understand that I-O assumes average cost and average emissions for product categories and emissions are scaled linearly based in dollars spent on each category of goods. The second major limitation is that all products produced within the same sector of the economy (of which there are about 420 in the EIO-LCA model used in this analysis) are assumed to have the same emissions per dollar of sector output. Other sources of uncertainty included: 1) geographic variation (e.g., accounting for the effect of imports), 2) time lag due to infrequent updates of emission factors, 3) source data uncertainty and error, 4) modeling error, and 5) user input error (Hendrickson, Lave, and Matthews 2010; Ochoa et al. 2005).

Given the inherent uncertainty in input-output analysis we considered it useful to compare results using two different models. Table 8 compares greenhouse gas emissions (metric tons CO_2e/yr) embodied in food, goods and services consumed by the average U.S. household using CEDA (Suh 2005) and EIO-LCA (Green Design Institute, C.M.U. n.d.), as well as the mean of the two datasets. Results for each category of emissions are generally within 10%, with the exception of red meat, for which results in EIO-LCA are about 30% higher. For the online version of the tool, we created customized emission factors for food, goods and services by dividing total annual emissions (mean of CEDA and EIO-LCA results) for each category in the model by average household consumption (in dollars, or calories for food) of the same category. Default consumption values for food are from USDA (Gebhardt et al. 2007). Default consumption values for goods and services are from the Consumer Expenditures Survey.

Table 8. Carbon footprint of average U.S. household using CEDA and EIO-LCA. Values in tCO_2e/yr

	CEDA	EIOLCA	Mean
TOTAL	21.0	21.8	21.4
Food (at home and away)	7.1	7.7	7.4
Cereals & bakery products	0.7	0.8	0.8
Dairy	0.8	0.9	0.8
Fruits & vegetables	1.0	0.9	0.9
Other food	2.4	2.3	2.4
Meat	2.1	2.8	2.5
Beef, Pork, Lamb, Veal	1.1	1.5	1.3
Processed meat & other	0.4	0.6	0.5
Fish & Seafood	0.1	0.1	0.1
Eggs and Poultry	0.5	0.5	0.5
GOODS	5.8	5.6	5.7
Appliances, Furniture and household equipment	1.1	1.0	1.1
Clothing	1.3	1.3	1.3
other goods	3.4	3.2	3.3
Medical supplies & medicine	0.7	0.6	0.7
Personal care & cleaning	0.9	0.9	0.9
Electronics, toys & recreation	1.5	1.4	1.5
Paper, office & reading	0.3	0.3	0.3
SERVICES	6.1	6.5	6.3
Education	0.9	1.1	1.0
Healthcare	2.4	2.4	2.4
Household maintenance & repair	0.1	0.2	0.1
Information & Communication	0.3	0.3	0.3
Miscellaneous	0.8	0.9	0.8
Organizations & charity	0.2	0.2	0.2
Personal business	0.6	0.6	0.6
Entertainment & recreation	0.9	0.9	0.9
TRANSPORTATION	2.1	2.0	2.0
Motor vehicle manufacturing	1.5	1.3	1.4
Vehicle parts	0.1	0.1	0.1
Vehicles services	0.5	0.5	0.5

Food

Emissions from food are based on daily caloric consumption of meat (in total or separately for beef, chicken & poultry, other meat, and fish & seafood), dairy, cereals, fruits and vegetables, and other food. Default daily diets are based on the U.S. national average diet of 2505 calories per day and 1,879 calories per day for children (Gebhardt et al. 2007). Users can select the number of adults and children in the household.

GHG emissions per calorie consumed of each food item are calculated using a top-down approach; all U.S. cradle-to-consumer GHG emissions from each food category (using EIO-LCA) are divided by all calories consumed of food in that category according to USDA (Gebhardt et al. 2007). This process involves creating a concordance table between BEA and USDA food categories and categories used in the calculator.

GHG emission factors for food categories are calculated as follows:

$$\$US_{food,i} * EF_{food,i} \ / \ 116.8M \text{ households}] \ / \sum [Calories_{food,i} * 365 days]$$

where total annual household emissions of each food category are created by multiplying total US dollars spent in each food category ($\$US_{food,i}$) by the weighted GHG emission factor ($EF_{food,i}$), divided by the number of US households (116.8M) in 2005. Total daily calories of each food item were aggregated from USDA data. Estimates of calories, emission factors and total emissions for each food item for adults, children and households for the typical U.S. household is provided in Table 9.

Table 9. Conversion of food calories per day to gCO2 per year

	Total	Adult	children		
number of people	2.50	2.50	0		
	Calories/day-adult	Calories/day-child	Calories/day-household	emission factor gCO2/calorie	tCO2/year-household
Meat, fish, eggs	543	407	1,357	4.52	2.240
Beef, pork, lamb	247	185	618	4.81	1.084
Poultry & eggs	165	124	413	4.10	0.617
Other (processed meat, nuts….)	58	44	145	7.39	0.392
Fish & seafood	73	54	182	2.23	0.148
Dairy	286	215	715	4.66	1.217
Grains & baked goods	669	502	1,673	1.47	0.896
Fruits & vegetables	271	203	678	3.03	0.748
Other (snacks, drinks, etc.)	736	552	1,841	3.73	2.507
					-
Total	2,505	1,879	6,263	3.26	7.608

As previously noted, we scale emissions based on household size, not based on expenditures on food. It is true that households in the upper income quintile spend more than twice as much on food than households in the lowest income quintile in the United States, as shown in Figure 3 below. Previous studies have assumed a linear relationship between expenditures on food and emissions, thus households in the upper income quintile would be assumed to purchase twice as much food (in dollars and physical units).

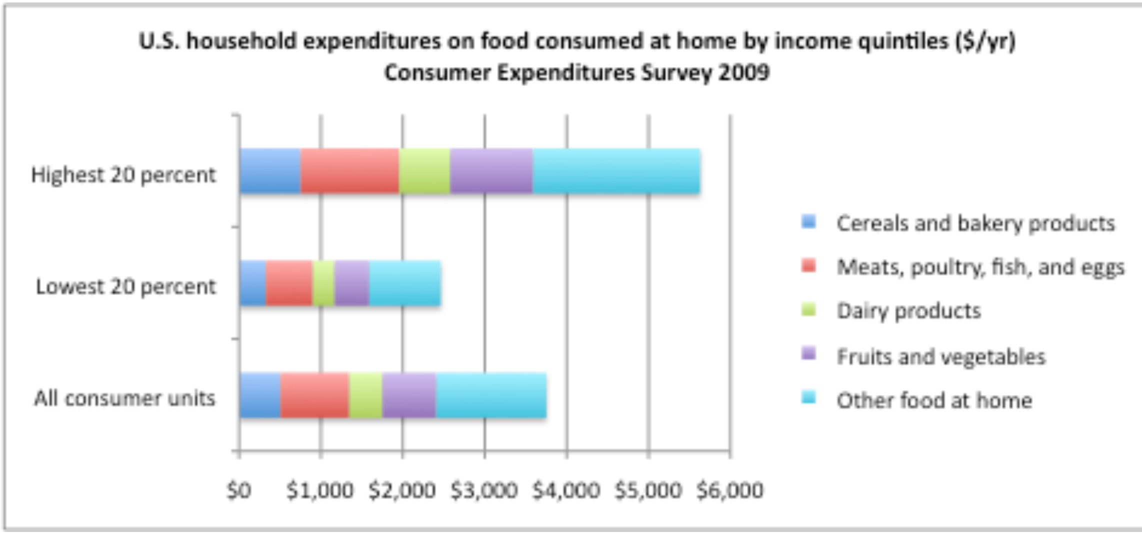


Figure 3. U.S. household expenditures on food consumed at home by income quintiles ($/yr)

Yet we see no evidence that upper income households actually eat more food than lower income households. For example, we know of no studies that suggest that higher income households in the United States are more overweight than lower income households (more likely the opposite may be true). We also do not find evidence that upper income households within the United States consume more meat and dairy. According the Consumer Expenditures Survey (2009), households in the highest income quintile spend 21% of their food budget on meat, compared to 23% for the lowest income quintile. Expenditures on all other food categories are essentially identical between income quintiles: cereals 13%; meat ~22%; dairy 11%; fruits & vegetables ~17%, other foods ~36% (Figure 4). Thus, while upper income households spend more than 2x on meat and dairy than lower income households, they also spend more than 2x on all other food categories as well; presumably, upper income households simply buy more expensive products. Given this remarkable uniformity it seems reasonable to assume identical diets, on a caloric basis, between households of different incomes within the United States. It may be important for future studies to at least consider a looser relationship between expenditures and diets.

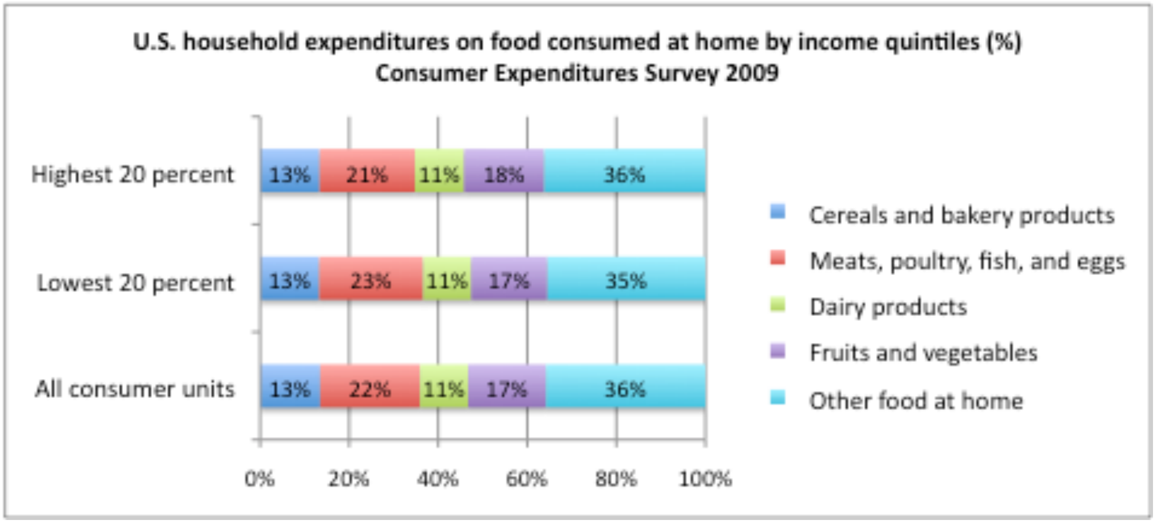


Figure 4. U.S. household expenditures on food consumed at home by income quintiles (%)

Food consumed in restaurants is considered to be similar to food consumed at home. Expenditures on food away from home are distributed proportionally between categories of food consumed at home. While upper income households spend much more on food away from home, we do not have evidence that this represents a larger fraction of total calories or that food consumed away from home is somehow different than food consumed at home. While there likely are important differences, this would be a topic for further research. It is also important to note that our study includes emissions from all purchased food, which is about 1.5 greater than food that is eaten, on a caloric basis (i.e., about one third of food is assumed to be wasted).

3.2.2. Methods for the greenhouse gas mitigation actions

Upon completion of the carbon footprint calculator, users of the online tool can build scenarios to reduce carbon footprints from different potential actions. For the purposes of this paper, we have selected a single basket of 13 actions (the full online tool (CoolClimate Network 2014) contains about 40 actions), including the following: 1) trading in two 20 mile-per-gallon (mpg) vehicles for 25 mpg vehicles, 2) reducing driving speed and aggressive braking, 3) keeping tires inflated and replacing air filters regularly, 4) telecommuting to work 20 miles per week instead of driving, 5) riding a bicycle 20 miles per week instead of driving, 6) taking public transit 20 miles per week instead of driving, 7) reducing air travel by 20%, 8) turning down the thermostat during winter, 9) turning up the thermostat during summer, 10) drying clothes on the line, 11) replacing five incandescent light bulbs with compact fluorescent light bulbs, 12) choosing an energy-efficient refrigerator, and 13) eating fewer calories, on average, with smaller portions of meat and dairy. Changing thermostat settings can also be interpreted to represent a potentially wide-ranging set of actions to reduce household energy consumption from heating and cooling. Where appropriate, we have accounted for interaction effects, e.g., simultaneously enhancing the fuel efficiency of the household vehicle fleet and reducing vehicle miles traveled. Actions were chosen based on prevalence in the literature (Dietz et al. 2009; Laitner and Ehrhardt-Martinez 2009) and the potential for greenhouse gas reductions.

Only actions that result in positive net present value (i.e., savings) are considered. The selected actions clearly represent only a subset of total possible actions. Thus, we do not attempt to present an estimate of total potential reductions from behavior change, as other studies have attempted to do (Dietz et al. 2009; Laitner and Ehrhardt-Martinez 2009), but rather seek to demonstrate GHG and financial savings of a set of actions across different geographic and demographic household types.

The Take Action page of the calculator allows individuals or households to estimate greenhouse gas and financial savings from a set of low carbon technology investments and behavior change opportunities, collectively called "Actions". Each individual Action is itself a mini-calculation tool, allowing users to adjust multiple settings (depending on the action) to reflect their personal options and preferences. Results are based on local energy and fuel prices (based on data from 28 major US metropolitan regions and all U.S. states), emissions from residential electricity production (at the level of U.S. states or utilities in the case of California), and local heating and cooling needs (for 250 U.S. regions).

Carbon footprint savings are presented in metric tons of CO_2 equivalent gases per year for each action and in total (including all pledged actions). Financial metrics include annual financial savings from changes in annual expenditures (e.g., reduced energy bills), 10-year net savings, upfront cost, 10-year net present value (NPV), return on investment (ROI) and simple payback period (in years). Users can adjust the discount rate (set to 8% by default) and annual inflation rate (set to 3% by default), which affects NPV and ROI. ROI is defined as ten year NPV over upfront cost. NPV is defined as:

$$NPV = \sum_{t=1}^{10} \frac{C_t}{(1+r)^t} - C_0 \tag{3}$$

where Ct is the financial saving at year t over 10 years, C_0 is the upfront cost in year 0 and r is the real discount rate of 5%.

Salvage value is assumed to be zero for all measures considered, only three of which include capital expenditures. In the case of motor vehicles, households are trading in existing used vehicles for other used vehicles so there is no additional salvage value. Similarly, refrigerators are not replaced, but rather Energy Star refrigerators are chosen at the time of purchase, rather than a non-Energy Star model. In the case of light bulbs, we assume there is no market value for used incandescent light bulbs.

Where appropriate, interaction effects are considered. For example, fuel efficiency is increased by purchasing more fuel-efficient models, reducing top highway speeds, reducing rough braking, replacing air filters and keeping tires inflated. This new fuel efficiency is used to estimate savings from reducing vehicle miles traveled. Since many home upgrades include interaction effects, e.g., replacing water heaters and reducing water consumption, we have limited the number of actions in homes to actions the do not interact. While this limited number of actions does not present the full spectrum of benefits from home retrofits, it does serve our primary purpose of demonstrating the effects of the same basket of carbon footprint reduction strategies across different household types and geographic locations.

Calculation of carbon footprint reductions and life cycle costs of measures

1. Buy more efficient vehicles by 5 mpg: Let m_1 be the miles household drives its vehicles per year = (21,200)($\$_{hh,t}$) / \$2,100, where 11,000 is the average vehicle miles traveled for the typical primary vehicle (2), ($\$_{hh}$) is the annual expenditures on gasoline for each household type, *t*, in the CEX and \$2,120 is the average U.S. household expenditures on gasoline. Carbon footprint savings (CFS) = $(m_1/ fe_c - m_1/ fe_n)(EF_{d+i})$, where f*e* is the fuel efficiency of current vehicle, *c*, and the new vehicle, *n*; EF_{d+i}, is the direct, *d*, and indirect, *i*, emission factor for gasoline. NPV = *equation 3*, where $C_t = (m_1 / p_c - m_1 / p_n)* g$, where g is the cost of fuel, assumed to be \$3 per gallon, and C_0 = \$4,000, covering sales tax, registration and other fees associated with trading in two vehicles for two more efficient vehicles of equal value.

2. Practice Eco-driving: CFS = $m / fe_n * EF_{d+i} - m / fe_{new} (EF_{d+i})$, where fe_n is the new fuel economy of the household's vehicle fleet after purchasing more efficient vehicles in Action 1, *m* = annual miles driven by household, $fe_{new} = fe + (fe_n)$(%HW)(%TS)(TS – HS)(0.01) + (fe_n)(1 - %HM)(TS - LS)(0.03), where 50% of vehicle miles, %HW, are highways miles (Davis, Diegel, and Boundy 2008), the driver reaches top speed 50% of the time, %TS, LW is 65 miles per hour, TS is 70 miles per hour, 0.01 is the amount reducing driving speed increases fuel efficiency, and 0.03 is the amount fuel efficiency increases by reducing rapid braking and acceleration (U.S. Department of Energy 2010). NPV = *equation 3*, where $C_t = m_5 / fe_n$ (G)– m / fe_{new} (G), and C_0 = 0.

3. Maintain vehicle(s): CFS = m / fe_n * 2(EF_d)(I), where I = fe_n (1+ 0.033 + 0.03), where 0.033 and 0.03 are the amounts fuel efficiency increases by keeping tires properly inflated and changing air filters regularly, respectively. NPV = equation 3, where where fe_n is the new fuel economy of the household's vehicle fleet after purchasing more efficient vehicles in Action 1 and Practicing Eco-driving in Action 2, *m* = annual miles driven by household, C_t = m / *fe* (I) and C_0 = \$20 for air filers.

4. Telecommute to work one day a week: CFS = $(m_2 / fe_n)(EF_{d+i})$ where fe_n is the new fuel economy of the household's vehicle fleet after Taking actions 1,2 and 3, Action 1, m_2 is the miles saved from telecommuting, which equals 1,400 miles per year (28 miles/day x 1day/week x 50 weeks/yr). NPV = equation 3, where $C_t = (m_2 / fe)$(g) and C_0 = 0.

5. Ride a bicycle 20 miles per week: CFS = $(m_3 / fe_n)(EF_{d+i})$ where fe_n is the new fuel economy of the household's vehicle fleet after Taking actions 1,2 and 3, m_3 is 1,000 miles per year (20 miles/week x 50 weeks/year). NPV = equation 3, where $C_t = (m_3 / fe)$(g) and C_0 = 0.

6. Ride the bus 20 miles per week: CFS = $(m_4 / fe_n)(EF_{d+i})$ – m4(EF_b) where fe_n is the new fuel economy of the household's vehicle fleet after Taking actions 1,2 and 3, $m_4 = m_3$ and EF_b is 107 gCO_2e per passenger mile (Ranganathan et al. 2004). NPV = equation 3, where Ct = (m_4 / *fe*)(g) – $\$_b$(m4), where $\$_b$ is 0, with the cost of public transportation assumed to be offset by reducing

vehicle depreciation and savings from parking, insurance, maintenance and other vehicle expenses.

7. Fly 20% less often: CFS = $m_7(EFair_{d+i})(0.20)$, where m_7 = miles housed travels by air each year, $EFair_d$ of 223 gCO_2e per passenger mile (Ranganathan et al. 2004) is multiplied by 2 to account for indirect atmospheric warming effects (Sausen et al. 2005). NPV = equation 3, where $C_t = m_7(0.20)(\$_{air})$, where $\$_{air}$ is \$0.12 per passenger mile (Bureau of Transportation Statistics 2010) and $C_0 = 0$.

8. Replace 5 lightbulbs with CFLs: CFS = $5(0.075kW - 0.020kW)(1825)(EF_{elec})$, where (0.075kW – 0.020kW) is the different power consumption of the bulbs, 1825 is the hours bulb left on per year, EF_{elec} is the emission factor for electricity of the state (eGRID, Supporting Materials). NPV = equation 3, where C_0 = \$1.25 (Energy Star 2010), $C_t = 5(0.075kW - 0.020kW)(1825)(\$elec) + \$3$, where \$elec is the price of electricity per U.S. state (U.S. Energy Information Administration 2010), \$3 is the net present value of replacing 4 incandescent bulbs over 10 years.

9. Turn down thermostat in winter: Let $E_{PU} = CI * HDD(HSF/1000)$, where, HDD is the average heating degree days per U.S. state (National Oceanic and Atmospheric Administration 2002), HSF is the heated square feet of the home, CI is the average US heating consumption intensity (U.S. Energy Information Administration 2005) for natural gas = 0.517. CFS = $E_{PU} * T_\Delta * 0.06 * 5470$, where T_Δ is the time-weighted average decrease in thermostat setting, assuming thermostat is turned down 8 degrees for 8 hours at night and 2 degrees for 10 hours during the day (U.S. E.P.A. 2010), 0.06 is the amount of heating saved per degree thermostat is turned down (U.S. E.P.A. 2010) and natural gas produces 5470 gCO_2/therm. NPV = equation 3, where $C_t = E_{PU} (T_\Delta)0.06(\$ng)$, where \$ng is cost of natural gas per U.S. state (U.S. Energy Information Administration 2014a) and $C_0 = 0$.

10. Turn up thermostat in summer: Let $E_{PU} = CI * CDD(CSF/1000)$, where CDD is the average cooling degree days per U.S. state (National Oceanic and Atmospheric Administration 2002), CSF is the conditioned square feet of home, CI is the average U.S. cooling consumption intensity for electricity = 6.283 (U.S. Energy Information Administration 2005). CFS = $E_{PU}(T_\Delta) 0.06 * EF_{elec}$, where T_Δ is the time-weighted average increase in thermostat setting, assuming thermostat is turned up 2 degrees for 10 hours on summer days and 4 degrees for 8 hours on summer nights, 0.06 is the amount of cooling saved per degree thermostat is turned up (U.S. E.P.A. 2010). NPV = equation 3, where $C_t = E_{PU} (T_\Delta)0.06(\$elec)$, where \$elec is cost of electricity per U.S. state (U.S. Energy Information Administration 2014b) and $C_0 = 0$.

11. Choose Energy Star refrigerator: This action assumes the household is ready to purchase a new refrigerator and chooses an Energy Star model over a non-Energy Star model. Let $E_{con} = (Fr + 1.63*Fz)(I) + Bl$, where E_{con} is annual electricity consumption, Fr is the refrigerator volume = 14.8 cubic feet, Fz is the freezer volume = 6.8 cubic feet, I = 9.8 kW per cubic foot, Bl = 276 kWh/yr. CFS = $(E_{con} - E_{es})(EF_{elec})$, where $E_{es} = 0.8(E_{con})$. NPV = equation 3, where $C_t = (E_{con} - E_{es})(\$elec)$ and C_0 = \$50.

12. Dry clothes on the line: CFS = $L (I) (EF_{elec})$, where L = 130 loads per year, I = 3.16 kWh per load. NPV = equation 3, where $C_t = L (I) (\$_{elec})$ and $C_0 = 0$.

13. Diet switching: Compares CFS of user's diet with lower carbon, and lower calorie diet. CFS = $\sum(m_cEFm_c, d_cEFd_c, c_cEFc_c, f_cEFf_c, o_cEFo_c)$ - $(m_nEFm_n, d_nEFd_n, c_nEFc_n, c_nEFc_n, f_nEFf_n, o_nEFo_n)$, where the household caloric consumption of meat, dairy, cereals, produce and other food items is multiplied by emission factors, EF, for each item (Supporting Materials) for the household current, c, and recommended new, n. NPV = equation 3, where C_t is the difference in cost between the two diets, with food prices from (C2ER 2014) and average caloric consumption of each food item from (Gebhardt et al. 2007).

Calculation of marginal abatement cost curves in main paper

The marginal abatement cost (MAC) curves in the main paper (Figures 10 and 11) show annual reductions of CO_2e for each measure on the x-axis and the levelized annual cost per metric ton of CO_2e conserved annually on the y-axis. Levelized annual cost is calculated by converting the net present value (NPV) of a project (see calculations above) into a uniform series of annual payments over the expected project lifetime. This is accomplished by multiplying NPV by a uniform capital recovery factor (UCRF)(Rubin and Davidson 2001).

$$UCRF = \frac{d}{1-(1+d)^{-n}}$$

Where d is the discount rate, which we assume is a 5% real discount rate for all measures. The area under the curves thus represents average annual financial savings of each measure.

Table 10. Emission factors and estimated uncertainty

Emissions category	Factor	Units	Estimated error (+/-)	Source
Gasoline (direct)	8,874	gCO2e/gal	1%	(1)
Gasoline (indirect)	2,307	gCO2e/gal	15%	(2)
Diesel (direct)	10,153	gCO2e/gal	1%	(1)
Diesel (indirect)	2,335	gCO2e/gal	20%	(2)
Vehicle manufacturing	56	gCO2e/mile	10%	(3)*
Average flight	223	gCO2/passenger-mile	10%	(4)
Short flights (<400 mi)	254	gCO2/passenger-mile	10%	(4)
Medium flights (400-1500)	204	gCO2/passenger-mile	10%	(4)
Long flights (1500-3000)	181	gCO2/passenger-mile	10%	(4)
Extended flights (>3000)	172	gCO2/passenger-mile	10%	(4)
Air travel indirect effects	1.00	x direct emissions	30%	(5)*
Public transportation	179	gCO2/passenger-mile	10%	(4)
Miles on bus	107	gCO2/passenger-mile	10%	(4)
Miles on commuter rail (light&heavy)	163	gCO2/passenger-mile	10%	(4)
Miles on transit rail (subway, tram)	163	gCO2/passenger-mile	10%	(4)
Miles on Amtrak	185	gCO2/passenger-mile	10%	(4)
Housing contruction	930	gCO2e/sq. ft.	20%	(3)
Electricity usage ($)	11,789	gCO2/$	19%	(7,8,10)
Electricity Indirect factor	0.08		15%	(11,12)
Electricity usage (U.S.average shown)	835	gCO2/kwh	5%	(7)
Natural gas usage (U.S.average shown)	4,317	gCO2/$	5%	(7,8)
Therms natural gas (U.S.average shown)	5,470	gCO2/therm	1%	(1)
Cubic feet natural gas (U.S.average shov	54.7	gCO2/cu.ft.	1%	(1)
natural gas indirect factor	0.14		15%	(11)
Fuel oil and other fuels	682	CO2e/$(2005)	15%	(3)
Water (California average)	444	gCO2e/person	15%	(9)
Water, sewage, wastes ($)	4,121	CO2e/$(2005)	15%	(3)*
Waste (California average)		gCO2e/person	15%	(9)
Food	2.92	gCO2e/calorie	15%	(3)*
Meat, fish & eggs	5.53	gCO2e/calorie	15%	(3)*
Beef, pork, lamb, veal	6.09	gCO2e/calorie	15%	(3)*
Processed meat & other	2.24	gCO2e/calorie	15%	(3)*
Fish & seafood	5.71	gCO2e/calorie	15%	(3)*
Eggs and poultry	4.27	gCO2e/calorie	15%	(3)*
Cereals & bakery products	1.45	gCO2e/calorie	15%	(3)*
Dairy	4.00	gCO2e/calorie	15%	(3)*
Fruits & vegetables	3.35	gCO2e/calorie	15%	(3)*
Other (snacks,beverages, alcohol,oils,etc.	2.24	gCO2e/calorie	15%	(3)*
Goods (sum of below)	565	CO2e/$(2005)	15%	(3)*
Clothing	750	CO2e/$(2005)	15%	(3)*
Furnishings, appliances, other household	614	CO2e/$(2005)	15%	(3)*
Other goods	971	CO2e/$(2005)	15%	(3)*
Medical	696	CO2e/$(2005)	15%	(3)*
Entertainment	1,279	CO2e/$(2005)	15%	(3)*
Reading	2,100	CO2e/$(2005)	15%	(3)*
Personal care & cleaning	954	CO2e/$(2005)	15%	(3)*
Auto parts	558	CO2e/$(2005)	15%	(3)*
Services (sum of below)	507	CO2e/$(2005)	15%	(3)*
Vehicle services	433	CO2e/$(2005)	15%	(3)*
Household maintenance and repair	134	CO2e/$(2005)	15%	(3)*
Education	1,065	CO2e/$(2005)	15%	(3)*
Health care	1,151	CO2e/$(2005)	15%	(3)*
Personal business and finances	197	CO2e/$(2005)	15%	(3)*
Entertainment & recreation	711	CO2e/$(2005)	15%	(3)*
Information and communication	291	CO2e/$(2005)	15%	(3)*
Organizations and charity	122	CO2e/$(2005)	15%	(3)*
Miscellaneous services	720	CO2e/$(2005)	15%	(3)*
Water Emissions per gallon	27.2	g CO2e/gal	15%	(9)

* emission factor has been modified (beyond unit conversion), as described elsewhere in this report
(1) EIA(a), Voluntary Reporting of Greenhouse Gases Program
(2) GREET, 2.8a
(3) EIO-LCA, CEDA, authors' calculations
(4) WRI/WBCSD, Greenhouse Gas Protocol
(5) Air indirect effects assumed 0.9 plus 0.1 from airports
(6) Housing consctrution: Assume 90 tCO2/50yrs=1.8tCO2/1800sqft
(7) eGRID
(8) EIA(b)
(9) California Air Resources Board
(10) Uncertainty parameter from Weber et al., 2010. See citation 72 for full reference
(11) Jaramillo et al., 2007. See citation 37
(12) Pacca, S., Horvath, A. 2002. See citation 36

3.3. Results and Discussion

Carbon Footprint Results and Discussion

The model produces default carbon footprint results for any combination of 78 regions (50 U.S. states and 28 major metropolitan regions), six household sizes, and 12 income brackets, for a total of over 2000 distinct household types. Figure 5 shows the carbon footprint of the average U.S. household, totaling 48 tCO_2e per year, or roughly 20 tCO_2e per person, for the baseline year of 2005. By comparison, average per capita emissions for the United States (total U.S. GHG inventory divided by the population) are about 24 tCO_2e per person. Emissions from government expenditures are not included in this assessment. Imports are assumed to have the same emissions as U.S. goods and services.

Direct emissions (primarily from transportation fuels, natural gas and fuel oil) account for 23% of total emissions, while indirect emissions account for 77%. Direct motor vehicle fuels, 9.4 tCO_2e, are the largest contributor to total emissions, followed by electricity: 7.1 tCO2e; meat: 2.5 tCO_2e; well-to-pump vehicle fuels: 2.5 tCO_2e; healthcare: 2.4 tCO_2e; “other food”: 2.4 tCO_2e; natural gas: 2.2 tCO_2e; and air travel (direct emissions plus indirect effects): ~2 tCO_2e.

Uncertainty parameters are calculated based on propagation of standard error estimates for each emission factor. These estimates are largely based on the authors’ judgment since published error estimates of emission factors and consumption are rarely available. Uncertainty is estimated at (1% for fuels but considerably higher (upward of 20%) for indirect emission factors from different data sets. Additional user error can also be expected for the online version of the tool.

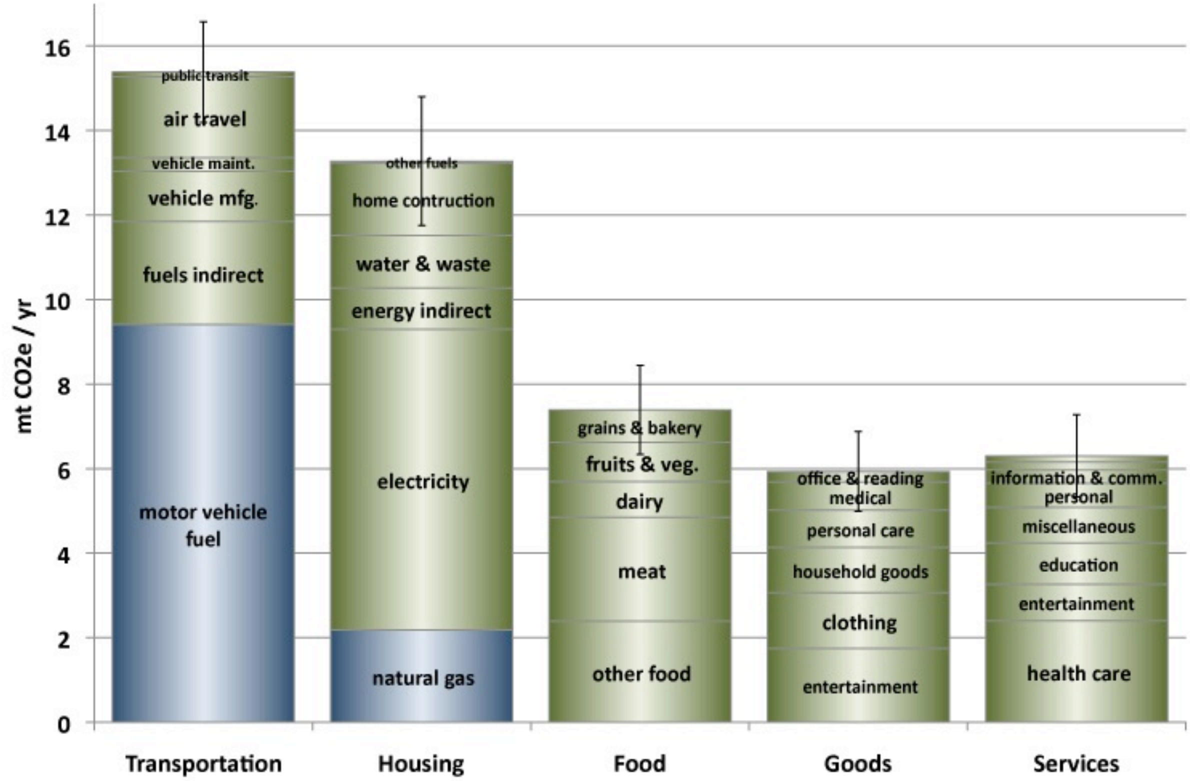


Figure 5. Total carbon footprint of typical U.S. household: 48 tCO2e/yr. Blue indicates direct emissions; green is indirect emissions.

The size and composition of carbon footprints vary substantially by location, income, and household size. Figure 6 shows average total carbon footprints of households of different sizes and income levels. A three-person household earning $100,000 per year has roughly double the carbon footprint of a three-person household earning $30,000 (60 tCO_2e vs. 30 tCO_2e). Household size also influences consumption and emissions. A two-person household earning $70,000 emits 52 tCO_2e per year, while a four-person household with the same income emits 64 tCO_2e; thus, doubling the number of people per household increases the carbon footprint by 23%, while decreasing per capita emissions by 60%. Increasing household size from two to four adds about another 10 tCO_2e per household, regardless of income level. Two-person households are generally less carbon intensive than two single-person households on a per capita basis; the combined carbon footprint of two individuals earning $55k per year is about 70 tCO_2e but only 60 tCO_2e for a two-person household earning $110k. Two single-person households have roughly the same carbon footprint as a typical household with two adults and two children.

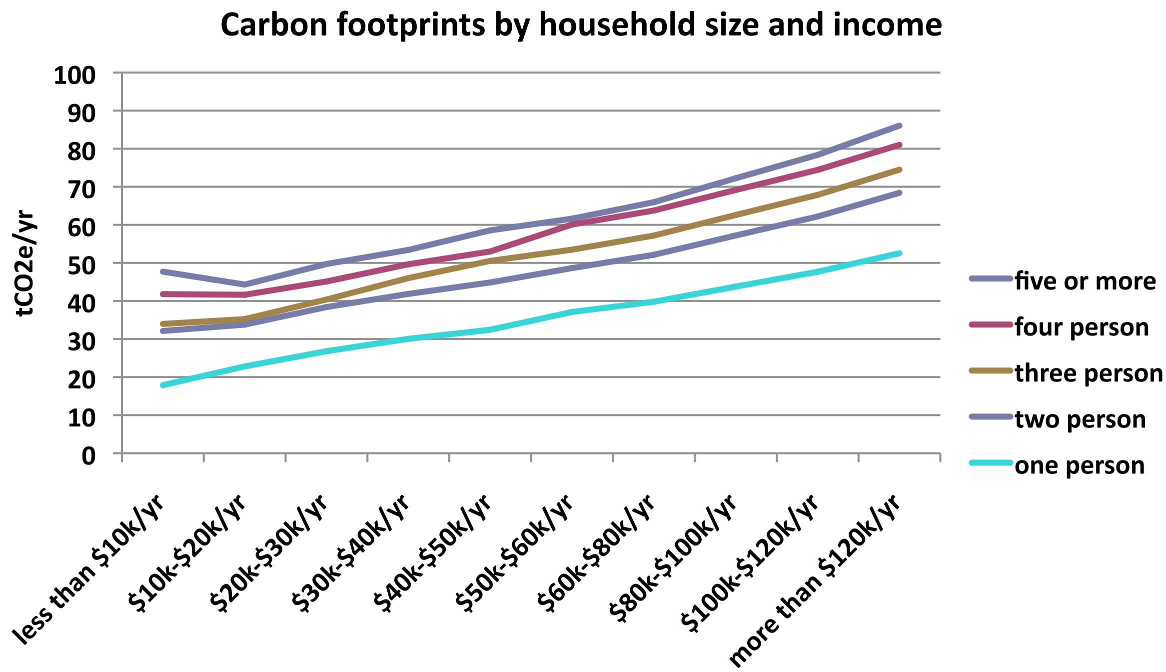


Figure 6. Carbon footprints by income bracket and household size

The composition of carbon footprints also varies considerably (Figure 7), with "housing" comprising 15-30%; transportation: 20-40%; food: 10-30%, between different household types. Carbon footprints of transportation fuel, natural gas, electricity, goods, and services increase predictably with income, with housing displaying low-income elasticity, and gasoline consumption increasing substantially as income rises. Food is a small contributor to total carbon footprints (~10%) for single-person households at high incomes but a large category of emissions at low incomes.

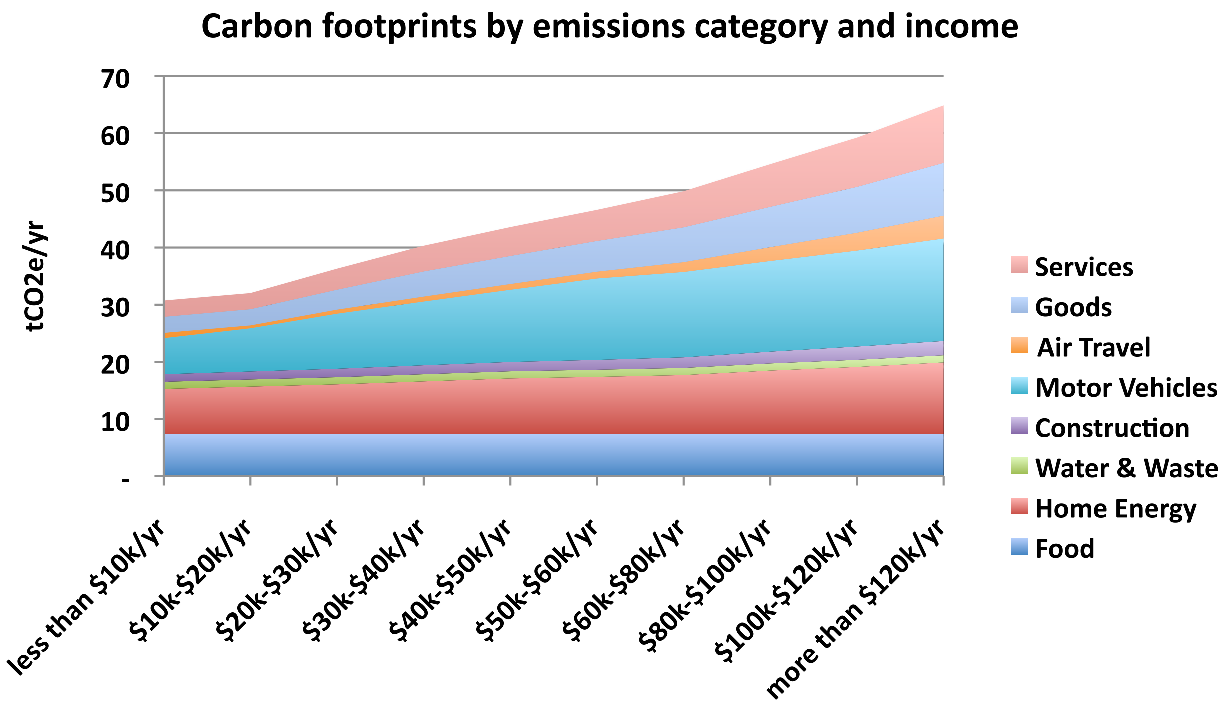


Figure 7. Carbon footprints by category of emissions and income bracket for average U.S. household size of 2.5 persons

The size and composition of carbon footprints varies markedly by location (Figure 8), ranging from 38 tCO_2e in Tampa to 52 tCO_2e in Minneapolis. Transportation footprints range from 8tCO_2e in Tampa to 18 tCO_2e in Los Angeles. Housing footprints (including direct and indirect emissions from energy, water, waste, and construction) range from 7 tCO_2e in San Francisco to 18 tCO_2e in Kansas City. Emissions from food (5-7 tCO_2e), goods (6-8 tCO_2e), and services (5-7 tCO_2e) are quite consistent between cities. Cities with the lowest carbon footprints tend to have low transportation footprints; however, many cities with low transportation footprints have relatively large housing footprints, e.g., Kansas City, Denver, St. Louis, Cleveland, Cincinnati, and Atlanta. By contrast, San Francisco and San Diego, the two cities with the lowest footprints from household energy (<4 tCO_2e for direct and indirect emissions from electricity, natural gas, other fuels) have large transportation footprints (~17 tCO2e, or nearly 40% of total emissions).

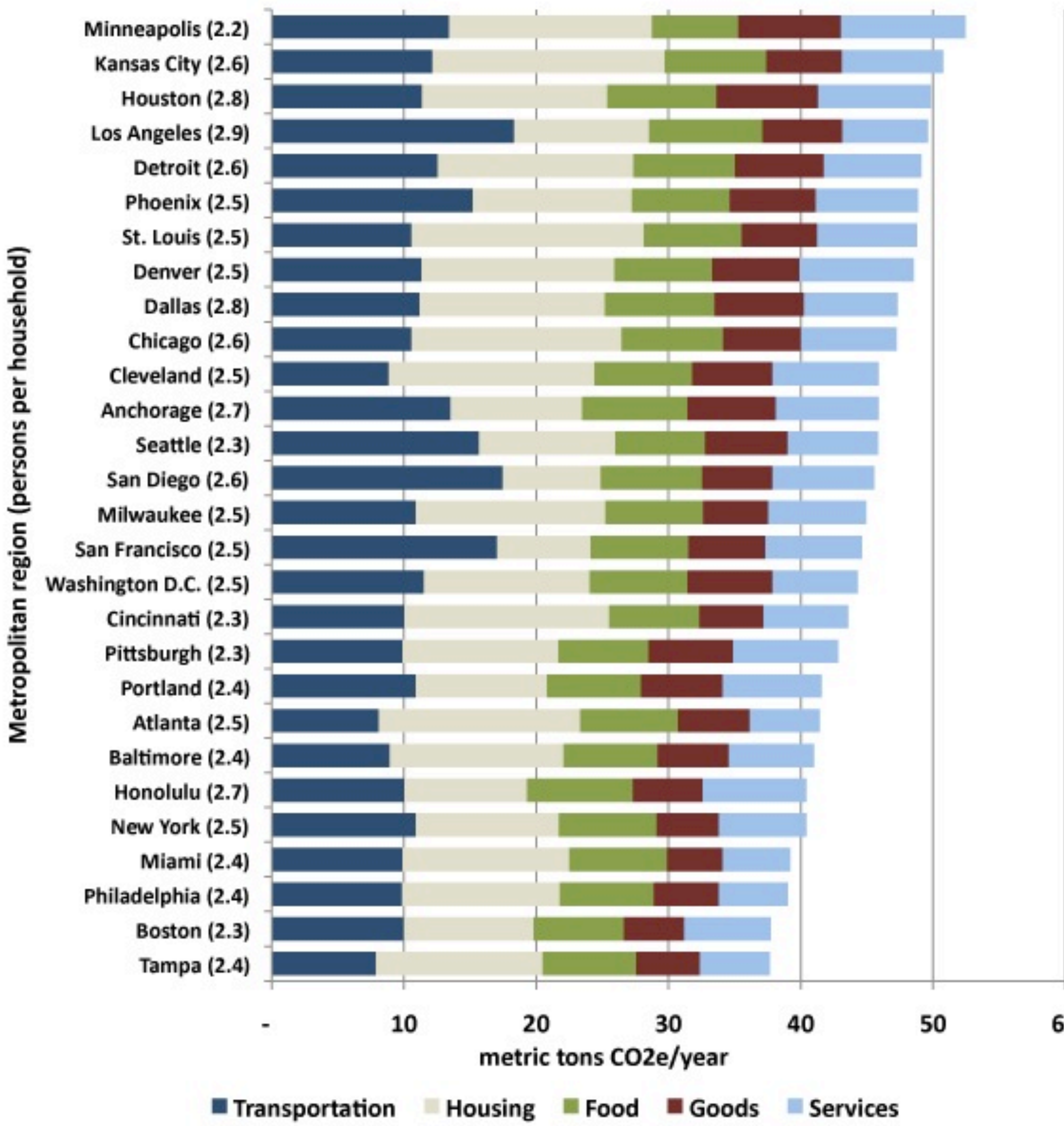


Figure 8. Household carbon footprints of the largest (by population) 28 metropolitan statistical areas in the U.S.

In contrast to differences at the household level, household size and income levels appear to have little effect on total carbon footprints of cities, as shown in Figure 9. While our model linearly scales emissions from food with household size, emissions from transportation, housing, goods, and services show no discernible difference as household size increases. Somewhat surprisingly, Minneapolis, which has the lowest household size (2.2 persons), also has the largest overall carbon footprint (52 tCO2e). Similarly, despite large differences in average annual household incomes (ranging from $51k in Miami to $75k in San Francisco), income has little effect on overall carbon footprints of cities. Several cities with relatively high household incomes have low overall carbon footprints (e.g., New York, Boston, and Baltimore). Higher population density, on the other hand, is strongly correlated with lower carbon footprints (r squared of 0.31), in line with other city carbon footprint studies (Brown, Southworth, and Sarzynski 2008; Glaeser and Kahn 2010; Kennedy et al. 2009).

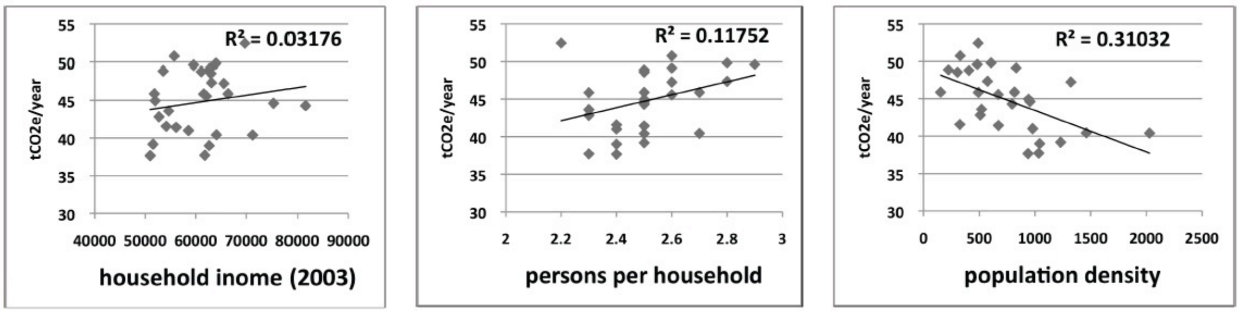


Figure 9. Household carbon footprints of U.S. metropolitan statistical areas by household income, persons per household and pop. density (persons / sq.mi.)

Climate Action Planner Results

The GHG and financial savings of each individual action are presented in Figure 10 in the form of a greenhouse gas abatement curve (Creyts 2007) with average annual GHG reductions on the x-axis and levelized annual cost per metric ton of CO_2e conserved on the y-axis. Under this scenario, the average U.S. household reduces its carbon footprint by 20%, or 9.5 tCO_2e per year, with an upfront cost of $4800, 10-yr net present value of $11,000 (at 8% discount rate and 3% inflation rate), and a payback of 2.6 years. Average financial savings are frequently greater than $100 per metric ton of CO_2e conserved for this set of actions. Changing diet results in the largest financial savings ($850/yr), largely from lower assumed daily caloric consumption (2200 vs 2500 calories for adults) and price differences between food items. Improving household fleet fuel efficiency by 5 miles per gallon results in 2.5 tCO_2e/yr, the largest carbon footprint reduction opportunity modeled. Emission reductions from household energy (1.7 out of 10 tons total) requires a larger number of individual actions to achieve GHG reductions, although some of these are one-time actions, such as replacing light bulbs and choosing an Energy Star refrigerator, which are arguably easier to implement than actions that require daily changes in behavior.

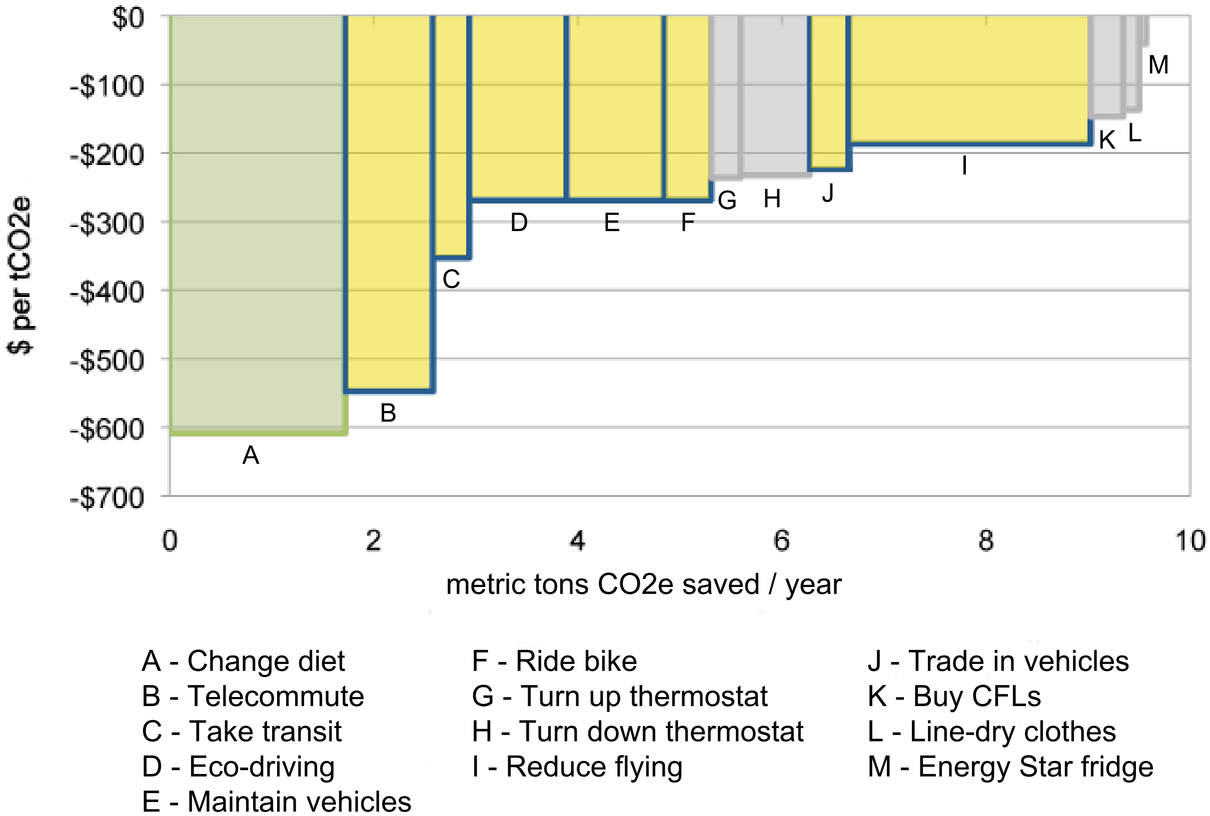


Figure 10. GHG marginal abatement curve for avg. U.S. household.

X-axis is annual GHG savings; y-axis is levelized annual cost of mitigation measures per metric ton of CO2 conserved. Green bars are for changing diets; yellow bars with blue outline are transportation; grey bars are household energy.

Presenting carbon footprints and climate action plan results for each of the >2000 household types in the model is not possible for this paper; however, Figure 11 presents results for two hypothetical households for illustration purposes. Household A is a 2-person household earning $90,000 per year, living in the San Francisco Bay Area. Household B is a 5-person household with $45,000 annual income, living in St. Louis. Climate action plan results to achieve a 20% GHG reduction are presented for each household.

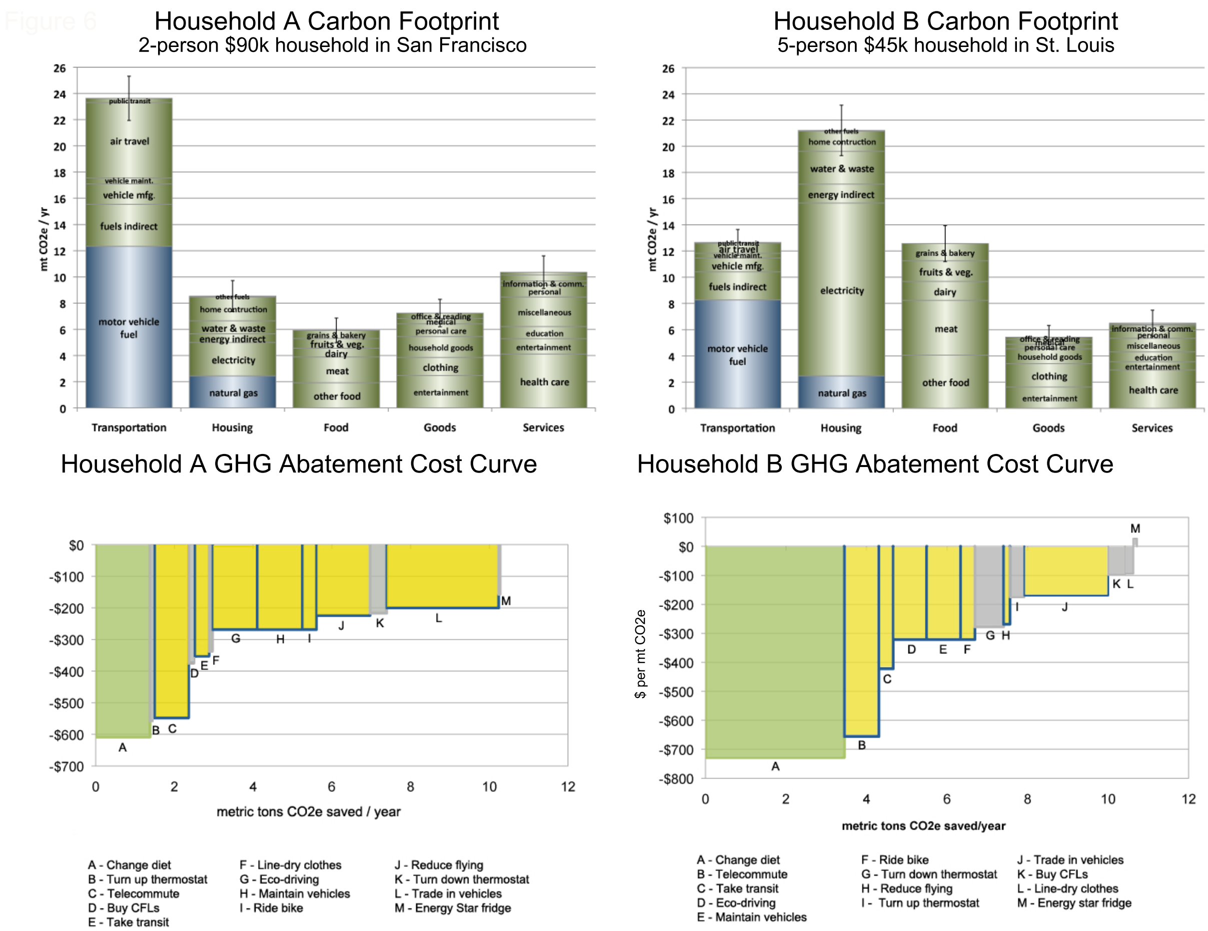


Figure 11. Carbon footprints and GHG abatement cost curves of example households

Carbon footprints and GHG abatement cost curves for example households. Household A is an upper income two-person household in the San Francisco Bay Area. Household B is a middle-income five-person household in St. Louis. In the upper figures, carbon footprints are shown for the major categories of emissions, with annual CO2e emissions on the y-axis. In the lower figures, X-axis is annual GHG savings; y-axis is levelized annual cost of mitigation measures per metric ton of CO2e conserved. Green bars are for changing diets; yellow bars with blue outline are transportation; solid gray bars are household energy.

The Carbon footprint of household A is dominated by emissions from motor vehicles and air travel. Emissions from household energy are about half of the U.S. average due largely to the relatively clean fuel mix of California's electricity grid and moderate San Francisco Bay Area climate. The household has essentially no emissions from cooling. Emissions from goods and services outstrip emissions from food due to the household's relatively high income and low number of household members.

The total ~20% footprint reduction potential modeled corresponds to about $2100/yr in potential financial savings. As could be expected, transportation dominates total carbon footprint reduction potential (8 out of 10 tCO_2e/yr total). The carbon footprint of household B is dominated by emissions from electricity. This is largely a product of high emissions per kWh of electricity in St. Louis and larger than average heating and cooling demands. Emissions from food also outstrip direct and indirect emissions from motor vehicles, due to the large household size. This modest income family has lower than average emissions from goods and services. The household can save $1400 per year and reduce its carbon footprint by almost 3 tCO_2e/yr by reducing overeating and waste from food and reducing the amount of meat, dairy, and nonessential food items consumed. Further savings of $500 per year and 3 tCO_2e/yr can be obtained by increasing the family's average fuel efficiency from 20 mpg to 25 mpg, reducing total vehicle miles traveled and practicing fuel-saving driving and vehicle maintenance habits.

The household has virtually no emissions from air travel. Carbon footprint savings of 2 tCO_2e can be achieved by adjusting the thermostat, replacing light bulbs, and line-drying clothes; however, financial savings are less than $200/yr due to relatively low energy prices in the state of Missouri.

Discussion of Climate Action Planner Results

Example households A and B demonstrate the utility of tailoring different carbon reduction policies and programs to different audiences based on the size and composition of household carbon footprints. For the typical two-person San Francisco household earning $90,000 per year, transportation carbon footprints outstrip household energy (electricity, natural gas, and other fuels) by more than five to one. For a typical five-person household in St. Louis, on the other hand, emissions from household energy are 1.5 times greater than emissions from transportation. While these represent rather extreme cases, Figures 11 (households A and B) demonstrate that the composition of carbon footprints can vary quite dramatically between different population segments, suggesting that one-size-fits-all messages, policies, and programs may be shortsighted and less effective than more targeted messages and programs. At the same time, assessing the actual potential for households to engage in lower-GHG lifestyles requires an understanding of the barriers preventing individuals from taking particular actions. For example, household B has roughly an equal opportunity to reduce emissions from transportation, household energy, and food. Increasing vehicle fuel efficiency may be attractive for the financial savings, although some families may perceive smaller, more fuel-efficient vehicles as being less safe. Reducing highway speed and aggressive driving, on the other hand, increases both safety and fuel efficiency. Saving household energy may also not be particularly appealing on financial grounds given the state's low energy prices (the high carbon footprint of electricity may be more effectively addressed through policies to reduce the carbon-intensity of electricity production, and potentially raising prices on energy). Programs targeted at encouraging low-carbon and healthy dietary choices, on the other hand, may hold potential for this household type. Reducing the households' food carbon footprint may be only a side benefit compared to the health benefits of reducing obesity, which is particularly prevalent in some lower income regions (Centers for Disease Control and Prevention 2014).

The upper income 2-person household in California (household A) presents a very different set of mitigation opportunities. Similar to Household B, the carbon footprint of this household is about 20% higher than the U.S. average (and 6 times the global average); however, the carbon footprint is dominated by transportation, both from motor vehicles and air travel. The total financial savings of $2100 per year are much less of an incentive for higher income household, particularly if these savings involve a large number of actions that may take considerable time and effort. Improving the household's average fuel efficiency from 20 to 25 mpg presents an attractive opportunity from a carbon footprint standpoint, saving 2.5 tCO_2e/yr. While the $225/yr in fuel savings may not be a large incentive, in environmentally conscious California clean cars can project higher social status, providing an important social incentive to drive fuel-efficient vehicles. Reducing air travel, or possibly purchasing carbon offsets, is an important aspect of this household's carbon footprint mitigation potential. While emissions from food are small relative to other emissions, focusing on the health and environmental benefits of vegetarian diets may be attractive as a social marketing technique in this geographic region and demographic.

While carbon footprint and GHG abatement opportunities vary greatly from one household type to the next, substantial GHG savings opportunities are possible across all geographic areas and demographic types modeled if behavior changes and energy efficient technologies are adopted. Financial and GHG savings potential from transportation are large across all household types; savings potential from diet switching depend largely on household size, and savings from housing depend largely on the price and GHG-intensity of household fuels, and energy consumption rates in different climate zones.

While consumption-based carbon calculators are a relatively new concept, we suggest that they can be valuable to reduce consumption-related greenhouse gas emissions by 1) encouraging a larger range of individual and household behavior changes, 2) reducing rebound effects and other unintended consequences associated with a more limited view of responsibility, 3) allowing individuals to benchmark their emission profiles with similar households, global averages and sustainable levels, 4) encouraging development of community action, 5) encouraging internalization of external costs related to greenhouse gas emissions and subsequently funding carbon mitigation projects, and 6) sending market signals to producers of goods and services to reduce supply chain and full life cycle emissions. Information campaigns alone have historically been noted to have had limited impact on changing consumer behavior;[4] indeed most policies are directed not at individuals but at community-scales, such as encouraging urban infill to increase population density. Nonetheless, large differences exist between cities with similar population densities and other characteristics, implying that information may play some role in affecting attitudes, norms, habits, and other determinants of behavior (Cohen and Murphy 2001; Stern 1992).

Sustainable consumption has been called both the "next wave" (Simons et al. 2001; Tukker 2006) and the "holy grail" (Jackson 2004) of environmental policy, highlighting both the enthusiasm for and the difficulty of actually implementing effective sustainable consumption programs and policies. At the same time, learning how to balance economic growth with environmental concerns is arguably the fundamental objective of sustainable development. Individuals can not learn to live more sustainably if they do not have information to help them make more environmentally benign decisions. Carbon footprint calculators are one mechanism to help consumers become aware of their impact on the planet and to target behaviors to reduce this impact over time. If carefully constructed, these tools may help realize some of promise and enthusiasm for sustainable consumption programs and policies.

Chapter 4: Spatial Distribution of U.S. Household Carbon Footprints[3]

4.1. Background

Demand for energy, transportation, food, goods and services drives global anthropogenic emissions of greenhouse gases (GHGs). Households in the United States alone are directly or indirectly responsible for between about 20% of annual global GHG emissions (Hertwich and Peters 2009) yet represent only 4.3% of total global population. In the absence of comprehensive national climate policy, U.S. states and over 1,000 U.S. mayors have committed to GHG reductions (Mayors Climate Protection Center 2008). In response, a new protocol exists for managing community-scale GHG emissions that emphasizes contributions from households. In order for compliance and voluntary policies to be effective, information is needed on the size and composition of household carbon footprints for all regions, at metropolitan, county, city and even neighborhood scales. As global urbanization accelerates, increasing by 2.7 billion people by 2050 (United Nations 2011) the lessons from the data-rich U.S. experience will have increasing importance for planning efforts in urban areas of the world's expanding list of mega-cities.

Previous research using a diverse set of methods focused largely on large metropolitan regions has shown that household carbon footprints (HCF) vary considerably, with energy, transportation or consumption comprising a larger share of the total and with households in some locations contributing far more emissions than others (Glaeser and Kahn 2010; Hillman and Ramaswami 2010; Sovacool and Brown 2010). For example, transportation in California comprises 35% of HCF, compared to 6% for household electricity, while electricity is frequently the largest single source of emissions in locations with predominantly coal-fired electricity (Jones and Kammen 2011). Income, household size and social factors have been shown to affect total HCF, while a large number of factors have been shown to contribute to household energy and transportation-related emissions (Baiocchi, Minx, and Hubacek 2010; Glaeser and Kahn 2010; Lenzen et al. 2006; Weber and Matthews 2008).

A number of studies suggest that geographic differences in emissions are in part explained by population density. Population-dense municipalities tend to be urban centers with employment, housing and services closely co-located, reducing travel distances, increasing demand for public transit, and with less space for larger homes. Early research by Newman and Kenworthy (1989) using data on 32 global cities, suggested a strong negative correlation between vehicle fuels and density (see Figure 16 below). More recent work using data from domestic and global cities has also seemed to confirm this relationship, although with more variance than previously thought (Karathodorou, Graham, and Noland 2010). One thread of research suggests that urban form (co-location of housing, employment and services) to be a more important factor (Cervero and Murakami 2010; Ewing and Cervero 2001). On the other hand, a recent by Echenique et al. (2012) suggests that neither density nor urban form result in large CO_2 benefits and these may be

[3] Reproduced with permission from: Jones, Christopher, and Daniel M. Kammen. 2014. "Spatial Distribution of U.S. Household Carbon Footprints Reveals Suburbanization Undermines Greenhouse Gas Benefits of Urban Population Density." *Environmental Science & Technology* 48(2): 895–902. Copyright 2014 American Chemical Society.

outweighed by other social costs such as crowding and higher rents, although this study has met with considerable controversy (Wilson and Chakraborty 2013).

These earlier studies have been limited to analyzing a small set of case studies, and the resulting conclusions are difficult to generalize beyond those included in the studies themselves. A large, nationwide dataset of all locations holds potential to re-assess the urban form hypothesis to more accurately describe the relationship between population, policy, urban form, and emissions. Our primary research questions are: 1) how much variability exists in the size and composition of household carbon footprints across all U.S. locations, and 2) how much of this variability can be explained by population density, income, home size or other factors contributing to carbon footprints in urban, suburban and rural areas?

In this work we developed econometric models to estimate household energy, transportation, consumption of goods and services and total carbon footprints at fine geographic resolution. Min et al. (2010) used national energy surveys to develop econometric models that could be applied at zip code tabulation areas to reasonably estimate household energy consumption. Other work in the UK used demographic and lifestyle data to estimate more comprehensive household carbon footprints at fine geographic resolution (Baiocchi, Minx, and Hubacek 2010).

We present a model that characterizes the size and composition of household carbon footprints for essentially every U.S. zip code, city, county, and U.S. state. Household carbon footprints are the greenhouse gas emissions required to produce, transport and dispose of all transportation, energy, food, goods and services consumed by households for one year. We use this information to develop high geospatial resolution household carbon profiles of each location and to analyze the effect of population density and level of urbanization on full life cycle GHG emissions.

4.2. METHODS AND MATERIALS

We use existing national household survey data to develop econometric models of demand for transportation, residential energy, food, goods and services. Independent variables used to predict household electricity, natural gas and other household heating fuels in the Residential Energy Consumption Survey (U.S. Energy Information Administration 2005) (n=4,363 households) include: energy prices, heating fuel type, heating and cooling degree days, structure of homes (number of rooms, percent single-detached, year home built), demographic information (income, number of household members, age of householder, race), home ownership, percentage rural or urban, Census divisions and U.S. state. Predictive variables for motor vehicles miles traveled (VMT) in the National Household Travel Survey (Bureau of Transportation Statistics 2002) (n=11,744 households) include number of vehicles owned, fuel prices, average time to work, percentage of commuters who drive to work, demographic information (income, number of household members, race), number of food and recreation establishments in the zip code, population density, Census region, and U.S. state. Independent variables for 13 categories of goods and 11 categories of services in the Consumer Expenditures Survey (Bureau of Labor Statistics 2008) (n=6,965 households) include household size and income. The total number of independent variables used in all models is 37, all of which were also compiled for zip codes for prediction purposes. Regression coefficients, t-statistics, and p-values for each independent variable, in addition to model summary statistics (adjusted r-squared), various tests of model validation and description of uncertainty are provided in the Supporting Materials.

The model regression coefficients were then applied to data known at the level of U.S. zip code tabulation areas (ZCTAs, or zip codes) in order to estimate demand for typical households of each category of consumption for >31k ZCTAs. Information on the demographic characteristics of population, the physical infrastructure of homes, travel patterns and economic activity are from the U.S. Census (U.S. Census Bureau 2013). Energy and fuel prices are from Energy Information Agency (U.S. Energy Information Administration 2014a) at the level of U.S. states (EIA). Heating and cooling degree-days were interpolated for each zip code from 5,500 NOAA weather stations (National Oceanic and Atmospheric Administration 2002) using Geographic Information Systems software. Diets for 15 categories of food for adults (first two household members) and children (remaining members) are from the USDA Nutrition database (Gebhardt et al. 2007). Demand was then multiplied by GHG emission factors, in carbon dioxide equivalents (Solomon 2007) for electricity (U.S. E.P.A. 2013), fuels (Office of Air Quality Planning and Standards 2013), and upstream emissions from fuels (Environmental Protection Agency 2013). Indirect life cycle emission factors for goods and services are from the CEDA economic input-output model (Suh 2005). Input-output life cycle assessment is widely used to approximate emissions from average goods per dollar of expenditures in the consumption literature (Lave and Matthews 2006). Emissions from water, waste and home construction are from previous work (Jones et al. 2012) and assumed to be the same for all households due to lack of regionally-specific data. We then created population weighted averages for each city, county and U.S. state. Zip codes were further classified into urban core, urban, urban fringe, suburban, rural fringe or rural in order to evaluate the effect of urban development on emissions using US Census data (Ingram and Franco 2012).

To be clear, the models do not measure consumption, but rather estimate electricity, natural gas, vehicle miles traveled, goods and services for average households in zip codes using econometric models of national household survey data. As such, the results should be considered benchmarks by which measurements may be compared. We are limited to only variables available for for zip codes, and have left out potentially important variables, such as fuel economy of vehicles and local energy policies. Local energy policies are reflected in the model only to a certain degree, by inclusion of some states as dummy variables.

The primary purpose of these models is prediction and not explanation or inference. Due to multicollinearity between independent variables, correlation coefficients should not be compared. In order to infer causation and explain the relative influence of independent variables we conducted a separate analysis of results for which we do explore the influence of multicollinearity (see Table 21 for a coefficient correlation matrix).

Detailed model results

This study uses econometric analysis of national household survey results to estimate household consumption at the level of U.S. zip code tabulation areas (ZCTAs), roughly equivalent to U.S. zip codes. Model variables were chosen only if equivalent data from U.S. Census or other sources are known for ZCTAs. There are 31,914 ZCTAs in the model, covering essentially all populated areas of the 50 U.S. States. Eight separate linear and log-linear models were constructed for different categories of household consumption: one for vehicle miles traveled using the National Household Travel Survey (Bureau of Transportation Statistics 2002), five for household energy using the 2005 Residential Energy Consumption Survey (U.S. Energy Information Administration 2005), one for food and another for other goods and services using the Consumer Expenditures Survey (Bureau of Labor Statistics 2008). Additional datasets and methods were used to fill in average consumption values for water, waste, and building construction following previous work (Jones et al. 2002).

The purpose of these models is prediction, and not inference. In order to improve the predictive power of the models we intentionally include collinear variables, e.g., the price of natural gas and the price of natural gas squared. As a result of collinearity, <u>the correlation coefficients or t-statistics of independent variables should not be compared.</u> Collinearity increases the goodness of fit of the model, which is necessary for more accurate prediction; however, collinearity confounds the relative contribution of independent variables as expressed by t-statistics or standardized beta coefficients. As long there is no interpretation of the regression coefficients, adding collinearity is a completely valid approach and is common in the literature for similar studies (Min, Hausfather, and Lin 2010). In future iterations of the models we may choose to add interaction terms, which would further increase collinearity in order to enhance the goodness of fit.

Electricity

Model results for household electricity are shown in Table 11.

Table 11. Log-linear multivariate regression model of household electricity consumption

	Unstanardized coefficients		Standardized coefficients		
	B	Std. error	Beta	t	Sig
(Constant)	4.82	0.64		7.6	0.000
PRICEKWH	-6.93	0.28	-0.43	-24.5	0.000
LNNHSLD	0.31	0.01	0.25	21.5	0.000
HEATKWH	0.35	0.02	0.22	19.8	0.000
TOTROOMS	0.09	0.01	0.24	18.6	0.000
CD65	0.00	0.00	0.21	17.5	0.000
KWHPSQU	1.93	0.18	0.17	10.9	0.000
CA	-0.26	0.03	-0.11	-10.3	0.000
LNINCOME	0.09	0.01	0.11	9.7	0.000
RURAL	0.14	0.02	0.08	7.9	0.000
DIV8	-0.218	0.03	-0.08	-7.8	0.000
DETTACHED	0.14	0.02	0.09	7.3	0.000
WHITE	0.122	0.02	0.08	6.0	0.000
REG2	-0.09	0.02	-0.06	-5.1	0.000
YEAR	0.001	0.00	0.05	4.4	0.000
BLACK	0.110	0.03	0.05	4.2	0.000
FL	-0.113	0.03	-0.04	-3.4	0.001
OWN	0.065	0.02	0.04	3.4	0.001
NY	0.086	0.03	0.03	2.5	0.011
AGEHHMEM1	-0.001	0.00	-0.03	-2.2	0.030

Dependent Variable: LNKWH
Weighted Least Squares Regression - Weighted by NWEIGHT

Model Summary

R	R Square	Adjusted R Square
0.78	0.608	0.607

ANOVA

	Sum of squares	df	Mean Square	F	Sig
Regression	33,916,985	19	1,785,104	357	0.000
Residual	21,839,244	4,362	5,007		
Total	55,756,229	4,381			

Dependent variable: LNKWH = natural log of electricity consumption in kWh/year

Independent variables:

- PRICEKWH = price of electricity in $/kWh (EIA average residential price for the year 2005 at level of U.S. states)
- LNNHSLD = natural log of number of household members
- HEATKWH = household heats with electricity
- TOTROOMS = number of rooms
- CD65 = cooling degree days, base 65 (NOAA, 1971-2000 30-year Climate Normal of over 5,000 weather stations interpolated to each zip code in GIS)(National Oceanic and Atmospheric Administration 2002)
- KWHPSQU = price of electricity squared

- CA = Dummy variable for state of California (chosen for inclusion because it was a significant variable)
- LNINCOME = natural log of household income
- RURAL = percentage of households categorized as rural
- DIV8 = U.S. Census division 8
- DETTACHED = percentage of single detached homes
- WHITE = percentage of households headed by race coded as White / Caucasian
- REG2 = U.S. Census region 2
- YEAR = year home built
- Black = percentage of households headed by race coded as Black / African American
- FL = Dummy variable for U.S. state of Florida (chosen for inclusion because it was a significant variable)
- OWN = percentage of households owned by occupant
- NY = Dummy variable for U.S. state of New York
- AGEHHMEM1 = Age of the head of household

Greenhouse gas emission factors for electricity are provided by the eGRID database at the level of eGRID subregions (U.S. E.P.A. 2013). The eGRID database aggregates emissions for each generator for thousands of power plants in the United States. Indirect “well-to-plug” emissions are assumed to increase generation emissions by 20% for electricity and natural gas, following the GREET model (Environmental Protection Agency 2013).

Natural gas

Heating fuel type varies significantly by region. Piped natural gas is typically not available in rural areas, and some large regions, including most of Florida. In order not to overestimate the use of natural gas in regions without natural gas connections we created three separate models to account for the fraction of homes in each zip code with different heating fuels.

Table 12. Log-linear model of natural gas consumption for percentage of homes with natural gas heating

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	16.458	0.814		20.228	0
HD65	2.57E-04	0	0.833	12.752	0
TOTROOMS	8.28E-02	0.006	0.27	13.652	0
PNGSQ	-1497.454	76.069	-0.294	-19.686	0
YEAR	-3.70E-03	0	-0.137	-8.839	0
BLACK	0.217	0.029	0.114	7.442	0
LNNHSLD	0.147	0.019	0.138	7.772	0
REG1	0.135	0.026	0.087	5.154	0
DETTACHED	0.103	0.026	0.077	3.922	0
HD65SQ	-1.30E-08	0	-0.361	-5.727	0
AGEHHMEM	2.27E-03	0.001	0.062	3.561	0
CD65	7.71E-05	0	0.1	4.612	0
OWN	7.00E-02	0.026	0.051	2.673	0.008
DIV4	-9.59E-02	0.034	-0.045	-2.849	0.004
DIV7	-9.88E-02	0.039	-0.048	-2.51	0.012
DIV8	-7.83E-02	0.035	-0.034	-2.218	0.027
LNINCOME	2.71E-02	0.013	0.037	2.039	0.042
Dependent Variable: LNBTUNG					
Weighted Least Squares Regression - Weighted by NWEIGHT					
Model Summary					
R	R Square	Adjusted R Square	rror of the Estimate		
0.72	0.518	0.515	68.63		
ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	11,554,688	16	722,168	153	0

Dependent variable: LNBTUNG = natural log of natural gas consumption in BTU/year

Independent variables:

- PNGSQ = price of natural gas squared (EIA average residential price for the year 2005 at level of U.S. states)(U.S. Energy Information Administration 2014a)
- TOTROOMS = number of rooms
- HD65 = heating degree days, base 65 (NOAA, 1971-2000 30-year Climate Normal of over 5,000 weather stations interpolated to each zip code in GIS)
- YEAR = year home built
- LNNHSLD = natural log of number of household members

- BLACK = percentage of households headed by race coded as Black / African American
- HD65SQ = heating degree days, base 65, squared
- REG1 = Census region 1
- CD65 = cooling degree days, base 65
- DETTACHED = percentage of single detached homes
- AGEHHMEM1 = Age of the head of household
- DIV 4 = Census division 4
- OWN = percentage of households owned by occupant
- DIV7 = Census division 7
- DIV8 = Census division 8
- LNINCOME = natural log of household income

Table 13. Log-linear model results for annual natural gas consumption for percentage of homes with gas heating

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	8.4	0.3		27.5	0.000
PNGSQ	-1,767	421.1	-0.690	-4.2	0.000
TOTROOMS	0.1	0.0	0.215	3.6	0.000
PRICENG	80.8	24.9	0.535	3.3	0.001
CA	0.4	0.2	0.164	2.8	0.006
LNNHSLD	0.3	0.1	0.159	2.7	0.007
FL	-0.7	0.3	-0.151	-2.6	0.010

Dependent Variable: LNBTUNG
Weighted Least Squares Regression - Weighted by NWEIGHT

Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
0.474	0.225	0.206	1.016

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	73	6	12.086	11.707	0.000
Residual	250	242	1.032		
Total	322	248			

Dependent variable: LNBTUNG = natural log of natural gas consumption in BTU/year

Independent variables:

- PNGSQ = price of natural gas squared
- TOTROOMS = number of rooms
- PRICENG = price of natural gas (EIA average residential price for the year 2005 at level of U.S. states)
- CA = Dummy variable for the state of California
- LNNHSLD = natural log of number of household members
- FL = Dummy variable for the state of Florida

Table 14. Log-linear model results of annual natural gas consumption for percentage of homes with heating oil as main heating fuel

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	10.63	0.43		24.74	0.00
REG2	-3.95	0.56	-0.62	-7.04	0.00
NY	-1.11	0.28	-0.39	-4.02	0.00
PNGSQ	-44.75	19.71	-0.20	-2.27	0.03
TOTROOMS	-0.13	0.06	-0.19	-2.00	0.05

Dependent Variable: LNBTUNG
Weighted Least Squares Regression - Weighted by NWEIGHT

Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
0.686	0.471	0.442	1.063

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	72.5	4.0	18.135	16.038	0.00
Residual	81.4	72.0	1.131		
Total	154.0	76.0			

Dependent variable: LNBTUNG = natural log of natural gas consumption in BTU/year

Independent variables:

- REG2 = Census region 2
- NY = Dummy variable for state of New York
- PNGSQ = price of natural gas squared (EIA average residential price for the year 2005 at level of U.S. states)
- TOTROOMS = number of rooms

Fuel Oil

Table 15. Linear model of annual fuel oil consumption for percentage of homes that heat with fuel oil

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	228.95	90.022		2.543	0.011
TOTROOMS	75.846	8.985	0.434	8.441	0
REG1	128.895	55.587	0.118	2.319	0.021
OWN	-164.353	48.794	-0.187	-3.368	0.001
AGEHHMEM1	2.836	1.043	0.134	2.72	0.007
DIV1	99.678	39.622	0.133	2.516	0.012
WHITE	-94.047	47.165	-0.099	-1.994	0.047

Dependent Variable: GALLONFO

Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
0.454	0.206	0.193	337.761

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	11,178,223	6	1,863,037	16	0.000
Residual	43,123,236	378	114,083		
Total	54,301,460	384			

Transportation

Motor vehicles

Vehicle miles traveled (VMT) of motor vehicles driven by residents is modeled using the National Household Travel Survey (Bureau of Transportation Statistics 2002). Similar to household energy, only variable available at the level of ZCTAs are included in the model.

Table 16. Log-linear model of annual household vehicle miles traveled

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	8.16	0.10		84.90	0.000
HHVEHCNT	0.34	0.01	0.39	45.60	0.000
LNHHINCV	0.17	0.01	0.16	20.29	0.000
AVE_TIMETOWK	0.00	0.00	0.10	14.16	0.000
LNHHSIZE	0.17	0.01	0.11	12.58	0.000
RACEWHITE	0.15	0.01	0.09	10.28	0.000
PCT_DRIVE	0.00	0.00	0.03	3.83	0.000
Cen_d_wsc	0.07	0.02	0.02	2.88	0.004
CEN_D_NE	-0.06	0.03	-0.02	-2.19	0.028
FOOD	0.00	0.00	-0.02	-2.67	0.008
CEN_D_W	-0.05	0.02	-0.02	-2.81	0.005
REC	0.00	0.00	-0.02	-2.90	0.004
CEN_D_M	-0.09	0.03	-0.02	-3.17	0.002
CEN_D_MA	-0.10	0.02	-0.04	-4.82	0.000
lnHTPPOPD	-0.03	0.00	-0.07	-8.18	0.000

Dependent Variable: LNVMT

Weighted Least Squares Regression - Weighted by WTHHFIN

Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
0.621	0.385	0.384	38.25

ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	10,748,754	14	767,768	525	0.000
Residual	17,158,757	11,730	1,463		
Total	27,907,512	11,744			

Description of Variables

- HHVEHCNT = number of vehicles per household

- LNHHINVCV = natural log of annual household income
- AVE_TIMETOWK = average minutes commuting to work
- LNHHSIZE = natural log of number of people in household
- RACEWHITE = percentage of residents whose race is "white" according to the U.S. Census
- PCT_DRIVE = percentage of commuters who drive to work instead of other modes
- Cen_d_wsc = West South Central Census Division
- CEN_D_NE = Northeast Census Division
- FOOD = number of food establishments in zip code
- CEN_D_W = West Census Division
- REC = number of recreation establishments in zip code
- CEN_D_M = Middle Census Division
- CEN_D_MA = Mid Atlantic Census Division
- LnPPOPD = natural log of population density (residents per square mile)

Annual CO_2e = VMT / mpg * EF gasoline

Where,

- VMT = vehicle miles traveled
- MPG = 22 miles per gallon
- EF gasoline = emissions factor of gasoline

All other household emissions

All other sources of household emissions are extrapolated from Jones and Kammen (2011) which categorizes average household consumption and carbon footprints for 6 household sizes, 12 income brackets and 28 metropolitan regions using the 2008 Consumer Expenditures Survey. All combinations of income bracket and household size total 72 distinct household types, with corresponding consumption profiles from the detailed survey. We apply a simple linear regression model using household size and income as the two independent variables for each of the following dependent variables:

Table 17. Categories, subcategories and depending variables in linear regressions of household consumption

Category	Subcategory	Dependent Variable
Transportation	Air Travel	Air Travel
Transportation		
Transportation	Public Transit	Bus
Transportation	Public Transit	Light Rail
Transportation	Public Transit	Heavy Rail
Transportation	Public Transit	Electric Rail
Housing		Water
Housing		Waste
Housing		Home Construction
Food	Meat & Fish	Beef
Food	Meat & Fish	Chicken & Poultry
Food	Meat & Fish	Fish & Seafood
Food	Meat & Fish	Lamb, Pork
Food	Meat & Fish	Other Meat
Food		Dairy
Food		Fruits & Vegetables
Food		Grains & Baked Goods
Food		Other Food
Goods		Clothing
Goods		Furniture & Appliances
Goods		Other Goods
Services		All Services

The Consumer Expenditures Survey of the Bureau of Labor Statistics (Bureau of Labor Statistics 2008) provides estimates of consumer behavior across all categories of consumer spending. The survey consists of a national quarterly sample of ~15,000 in-person interviews and 3,200 detailed diaries. It is important economic instrument developed by the BLS to maintain the Consumer Price Index (CPI) as well as the CEX, which is widely used in economic studies, including consumption-based greenhouse gas accounting. Following our previous work (Jones and Kammen 2011) food is estimated at 3 metric tons CO_2e per person.

Validation of Model Results

Evaluating the predictive power of the model for all geographic locations is not possible due to lack of comparable data. We therefore compared model results to several existing studies and datasets in order to better understand how well the model predicts consumption and emissions at different geographic scales. Figure 12 summarizes results for four model comparisons for household electricity and natural gas for California counties (upper figures), vehicle miles traveled for U.S. states (lower left), and total household carbon footprints for 28 metropolitan regions (lower right). Actual natural gas consumption is within 20% of predicted values for 26 of the 30 counties, and within 15% for 23 counties. Actual electricity consumption is within 20% of predicted values for 23 of 30 counties. Actual VMT is within 20% of predicted values for 80% of U.S. states. The model tends to somewhat underestimate electricity and VMT for locations with relatively high values, thus differences between urban cores and suburbs described in the main paper are likely larger than estimated in this study. Total emissions for metropolitan statistical areas are well aligned, but somewhat higher in the current study compared to our previous work, which relied on the Consumer Expenditures Survey (CES) to estimate consumption. The difference may be due to weighting of sampled data, e.g., the CEX may have included more persons in urban cores, while our current dataset is a population-weighted average of all persons in all zip codes within metropolitan statistical areas. Model results are comparable to other published studies. In particular, energy results are quite similar to Min et al. (2010) and the goodness of fit (r-squared) of the transportation model is similar to Glaeser and Kahn (2010).

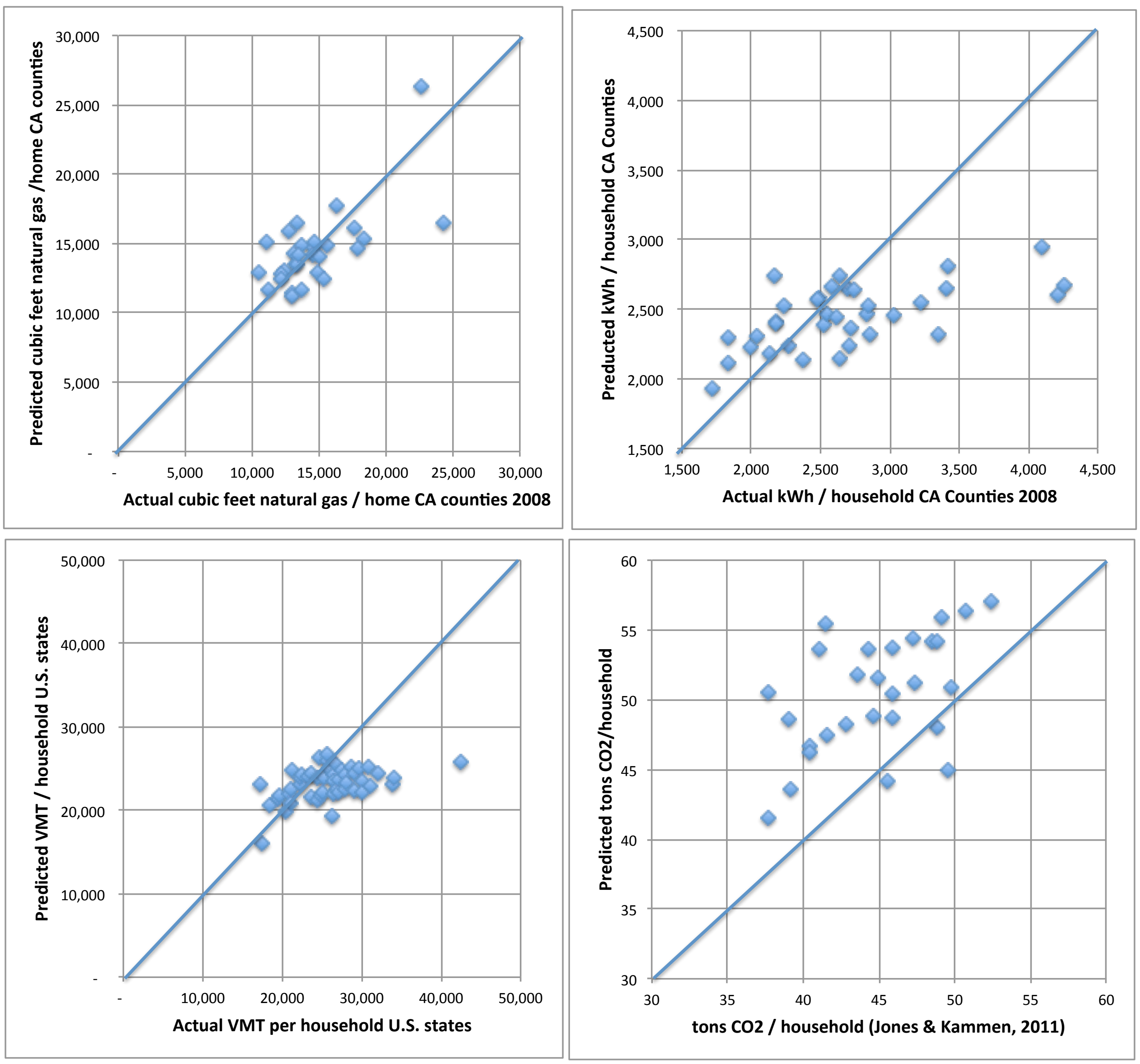


Figure 12. Comparison of current results with other datasets.

Upper left figure compares predicted natural gas consumption to average household natural gas consumption in 30 most populous California counties (California Energy Commission 2013). Upper right figure compares predicted electricity with California county data. Lower left figure compares predicted vehicle miles traveled to average household VMT for 50 U.S. states (Department of Transportation 2014b, 5–3). Lower right figure compares total household carbon footprints with results from previous work (Jones and Kammen 2011) using the Consumer Expenditures Survey for 28 metropolitan regions.

Herein we present results highlighting regional differences and explore the impact of population density and suburbanization. The dataset could also support a range of other potential results not included in this paper, including rankings, composition comparisons, mitigation analysis, efficiency ratings based on reported energy usage, quantitative spatial analysis, and comparison with source emissions. Interested readers are encouraged to visit the project website (CoolClimate Network 2014) to view detailed maps and results for any zip code, city, county or U.S. state.

4.3. RESULTS

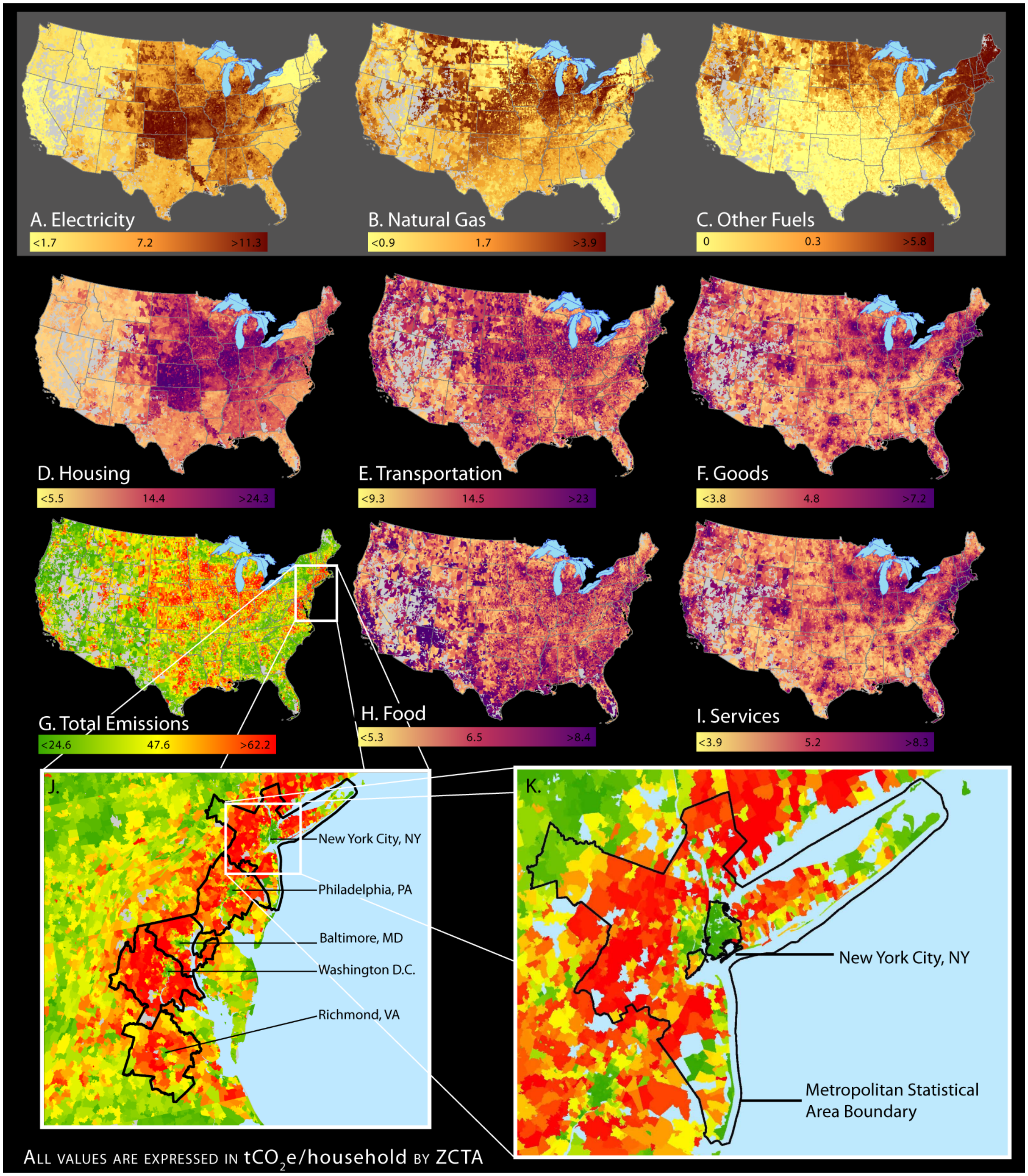


Figure 13. Average household carbon footprints (HCF) from different sources, and blowups of East Coast metropolitan areas.

HCF from (A) electricity, (B) natural gas, (C) fuel oil and other fuels, (D) housing = A+B+C + water, waste and home construction, (E) transportation, (F) goods, (H) food, (I) services, and (G) total = D+E+F+H+I. Transportation includes motor vehicle fuel, lifecycle emissions from fuel, motor vehicle manufacturing, air travel direct and indirect emissions, and public transit. Scales below each map show gradients of 30 colors, with labels for upper value of lowest of quantile, median value and lowest value of highest quantile, in metric tons CO_2e per household, for zip code tabulation areas (ZCTAs). These maps show broad regional patterns of average household carbon footprints in each ZCTA. East Coast metropolitan statistical areas (J), with a

larger map of New York metropolitan area (K, outer line) and New York City (K, inner line) highlight the consistent pattern of relatively low GHG urban core cities and high GHG suburbs.

The broad regional patterns of household carbon footprints across the contiguous United States are shown in Figure 13 in aggregate, and for the home energy, transportation, goods, services, and food components. It is important to note that this map allocates all emissions to households at the point of residence (a consumption perspective), and not where emissions physically enter the atmosphere (a production perspective). All data are presented on a per household basis, but show similar spatial patterns when viewed on a per capita basis. The Midwest, non-coastal East and much of the South have relatively high GHG emissions from electricity (1a), while the entire West and Northeast regions of the country show relatively low electricity emissions, due primarily to low carbon-intensity of electricity production. Natural gas (1b) and other heating fuels (1c) are concentrated in colder regions of the country, including the Midwest, Northeast and parts of the Pacific. Combining all energy emissions along with the life cycle emissions of fuels, water, waste and home construction into a single metric, "housing," (1d) presents a more comprehensive view of the contribution of homes to HCF than when considering energy components independently. Viewed through this lens, the Midwest and much of the South have relatively high emissions, so do parts of the Pacific and much of the Northeast. HCF from transportation (1e), goods (1f), food (1h), services (1i) and in total (1g) are widely distributed across the United States with no distinct broad regional patterns; however, the largest concentrations of HCF are surrounding metropolitan regions. When viewing HCF maps at regional spatial scales it is evident that GHG hotspots surrounding metropolitan regions have low carbon footprint cores, with rural areas exhibiting average to low carbon footprints. Figure 13j demonstrates this effect for East Coast metropolitan statistical areas. This pattern holds across the United States, with larger cities exhibiting the strongest urban/suburban differences, e.g. the New York metropolitan statistical area (1k).

A number of factors account for differences between household carbon footprints in urban cores and suburbs. Figure 14 shows transportation, energy, goods and total household carbon footprints for zip codes in the Atlanta metropolitan area. All data are in metric tons CO_2e per household with colors reflecting the individual scales for each map, consistent with Figure 13. Outer dark line is the boundary of the 28-county metropolitan statistical area. Inner line is boundary of the city of Atlanta. The maps demonstrate relatively low carbon urban cores and high carbon suburbs for all major sources of household carbon footprints. Atlanta was chosen as the example for this figure because it is the most populous landlocked MSA. All other large MSAs show very similar patterns. The zip codes with the highest energy-related emissions are concentrated in a tight band of suburbs between 15 and 45 miles from the city center. Despite having the same weather, energy prices and carbon-intensity of electricity production, suburbs still exhibit noticeably higher energy-related emissions. Geographic differences are most pronounced for transportation-related emissions, which range from <10 tCO_2e per household in the urban core to >25 tCO_2e in the most distant suburbs. Income and household size contribute to larger consumption-related carbon footprints in suburbs. The combined result is distinct carbon footprint rings surrounding urban cores, with suburbs exhibiting noticeably higher HCF.

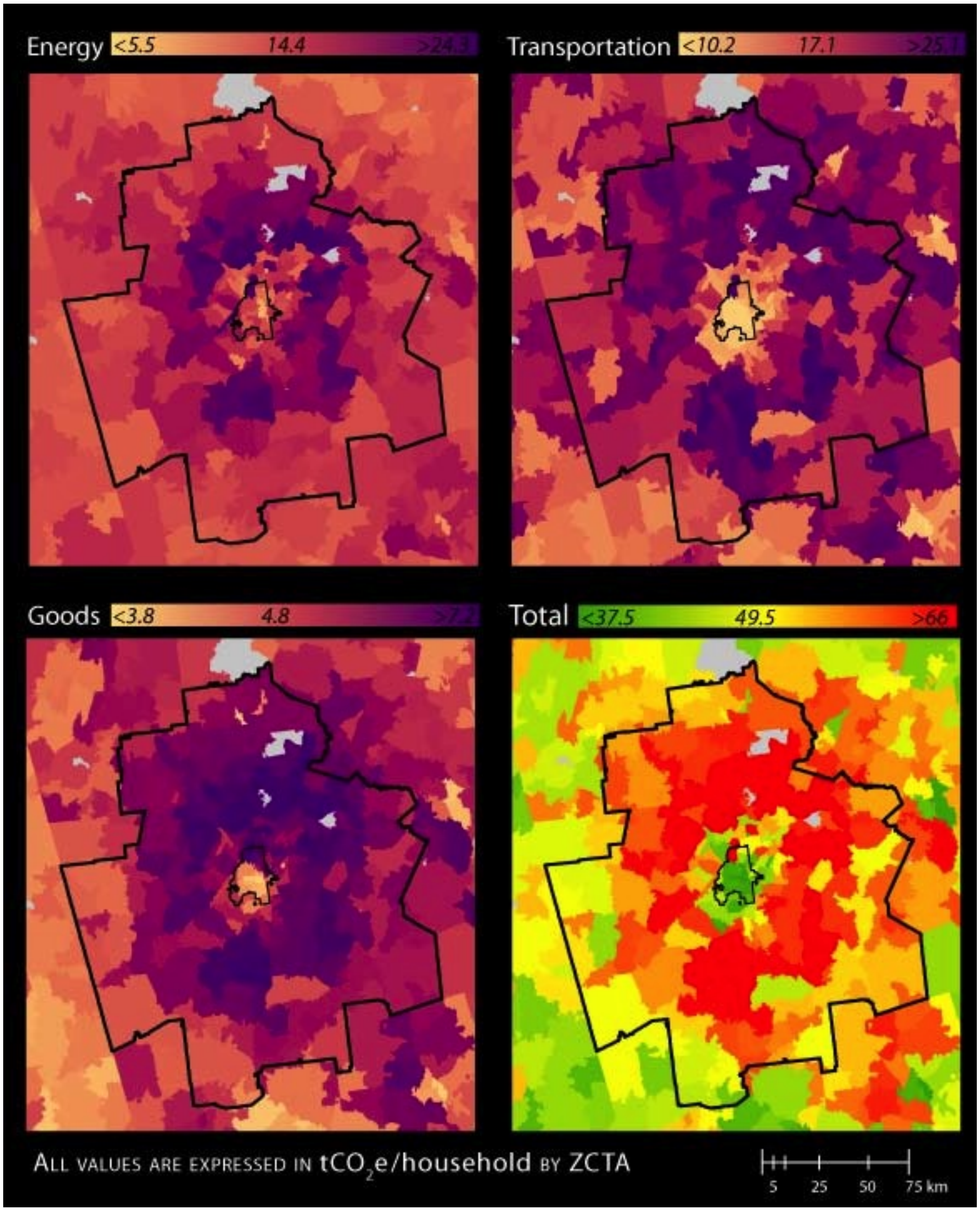


Figure 14. Composition of household carbon footprints in Atlanta for Energy, Transportation, Goods and Total

This large dataset allows for a more complete understanding of the effect of population density on communities than previous work limited to a number of cities. In Figure 15, total household carbon footprints are plotted against $\log_{10}$ of population density for all zip codes (a), cities (b), counties (c), metropolitan statistical areas (d), urban core cities (e) and the 100 most populous urban core cities (f). Carbon footprints in 10,093 cities (and also zip codes) are widely dispersed, with standard deviation of 9.2 and mean 52.0 tCO_2e. In contrast, carbon footprints of entire metropolitan statistical areas are quite similar, 48 tCO_2, S.D. 3.8. The red lines show mean HCF for all locations within each tenths place along the x-axis. Mean HCF, standard deviation and range increase moderately until a threshold of about 3,000 persons per square mile is reached (3.5 on the x-axis), after which mean HCF decreases logarithmically by about 10 tCO_2e for each tenfold increase in population density. Linear trend lines plotted for each chart reveal virtually no correlation between population density and household carbon footprints (r-squared = 0.001 for zip codes and cities, 0.01 for counties and metropolitan areas), with the exception of the 100 largest cities (r-squared = 0.29). Other possible trend lines produce similar results, with or without a log x-axis. If plotting only the mean carbon footprints of highly dense cities, it is possible to find strong correlations between population density and transportation emissions or total HCF; however, this correlation completely disappears when considering all cities or metropolitan regions.

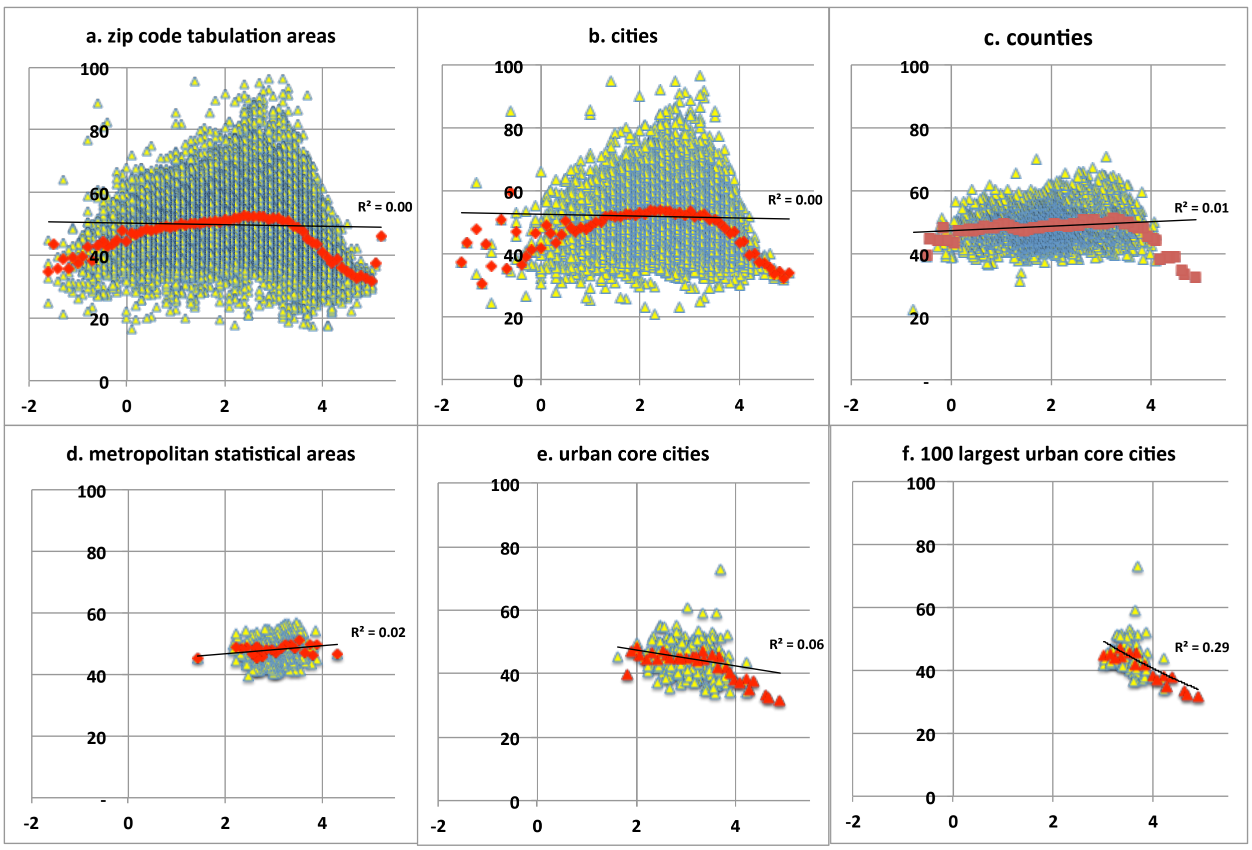


Figure 15. Average household carbon footprints of cities and other population scales.

Average household carbon footprints (HCF) in (a) 31,531 zip code tabulation areas, (b) 10,093 U.S. Census cities and towns, (c) 3,124 counties, (d) 276 metropolitan statistical areas, (e) 376 urban core cities, and (f) 100 largest urban core cities, by log_{10} of population per square mile (log of population density). The red line in each figure is the mean of all HCF for that population density, calculated to the tenths place. Linear goodness of fit trend lines show no correlation between population density and HCF, with the exception of the 100 largest urban core cities, R-squared = 0.29. Mean HCF decreases only after ~3,000 persons per square mile (or 3.5 on the x axis).

This finding is in contrast to previous research using a far more limited number of cities. Reprinted in Figure 16 below is Newman and Kenworthy's 1989 plot of household gasoline consumption per population density of 32 global cities. This figure has been widely cited as demonstrating a strong correlation between population density and fuel consumption and greenhouse gas emissions (with 651 Google Scholar citations for their 1989 Journal of American Planning Association paper (Newman and Kenworthy 1989) and 1249 Google Scholar citations for their book (Newman and Kenworthy 1999), which also contains the figure, as of this writing).

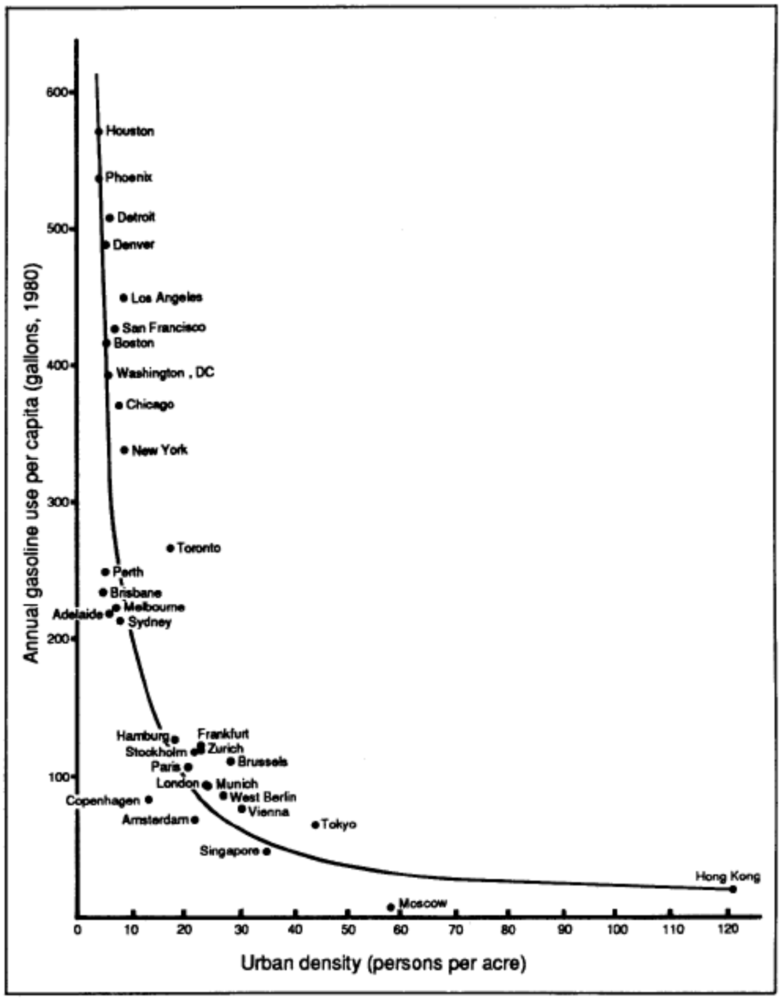


Figure 16. Gasoline per capita vs. population density (1980). Reprinted from Newman and Kenworthy (1989)

For comparison, we have superimposed our results in Figure 17. The much larger set of cities included in our dataset shows a large range of gasoline consumption and very low correlation with population density (R^2=0.11). However, if only considering average cities for each population density (red diamonds), there is a strong correlation (R^2=0.86). This comparison demonstrates the effect of including all cities vs only selected cities in such an analysis.

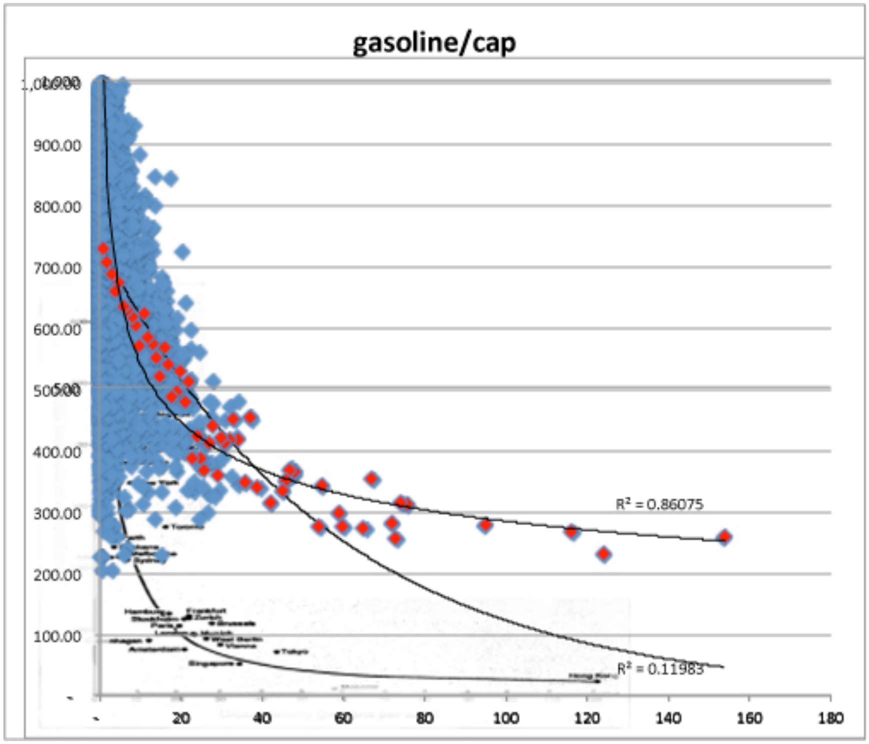
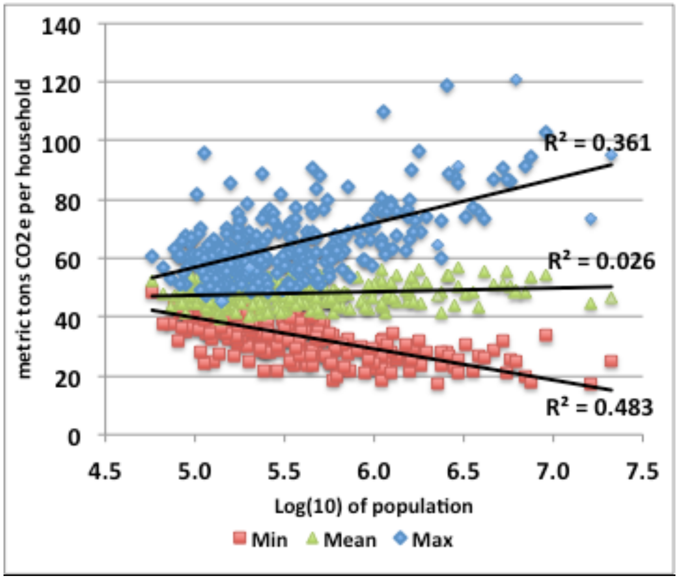


Figure 17. Gallons per capita in U.S. cities (blue diamonds), average gallons per capita for each tenths place on the x-axis (red diamonds) and results form Newman and Kenworthy (bottom line)



	Min	Mean	Max	Max/Min
10 smallest	40.3	46.7	58.8	1.5
50 smallest	41.5	47.9	61.4	1.5
100 smallest	39.8	47.7	59.7	1.5
All MSAs	34.1	48.1	65.0	1.9
100 largest	27.8	48.6	72.5	2.6
50 largest	26.1	49.5	79.9	3.1
25 largest	25.2	50.1	85.5	3.4
10 largest	24.6	50.6	92.9	3.8

Figure 18. Min, mean and max carbon footprints of zip codes within 276 metropolitant statistical areas (y-axis) by total population (x-axis)

In agreement with population density hypotheses, large, dense metropolitan areas do contain locations in city cores with very low HCF compared to smaller, less dense cities, but they also contain suburbs with relatively high HCF, more than offsetting the benefit of low carbon areas in city centers. Figure 18 shows the min, mean and max household carbon footprints of zip codes within each metropolitan statistical area. There is a strong negative correlation between population and min values (r-squared = 0.483) but also a strong positive correlation between population and max values (r-squared = 0.361). As metropolitan size increases the difference between the lowest and highest HCF locations grows from 1.5x for small metropolises to 4x for the largest. Thus, while the 25 most populous MSAs contain locations with 50% lower HCF than average, there is a small but noticeable trend of higher overall household carbon footprints in larger metropolitan areas due to the influence of outlying suburbs. The two largest metropolises, New York and Los Angeles, break this trend by demonstrating lower than average HCF.

Figure 19 is the same plot with population density on the x-axis instead of population. Linear goodness of fit lines are drawn between min, mean and max values, including R-squared for each line. Results from six metropolitan regions are labeled, including Jamestown NJ (lowest mean HCF), Chico, CA (second lowest mean HCF), Portland, OR (includes zip code with lowest

HCF), Minneapolis, MN (highest mean HCF), Philadelphia, PA (includes zip code with highest HCF), and New York, NY (highest population density).

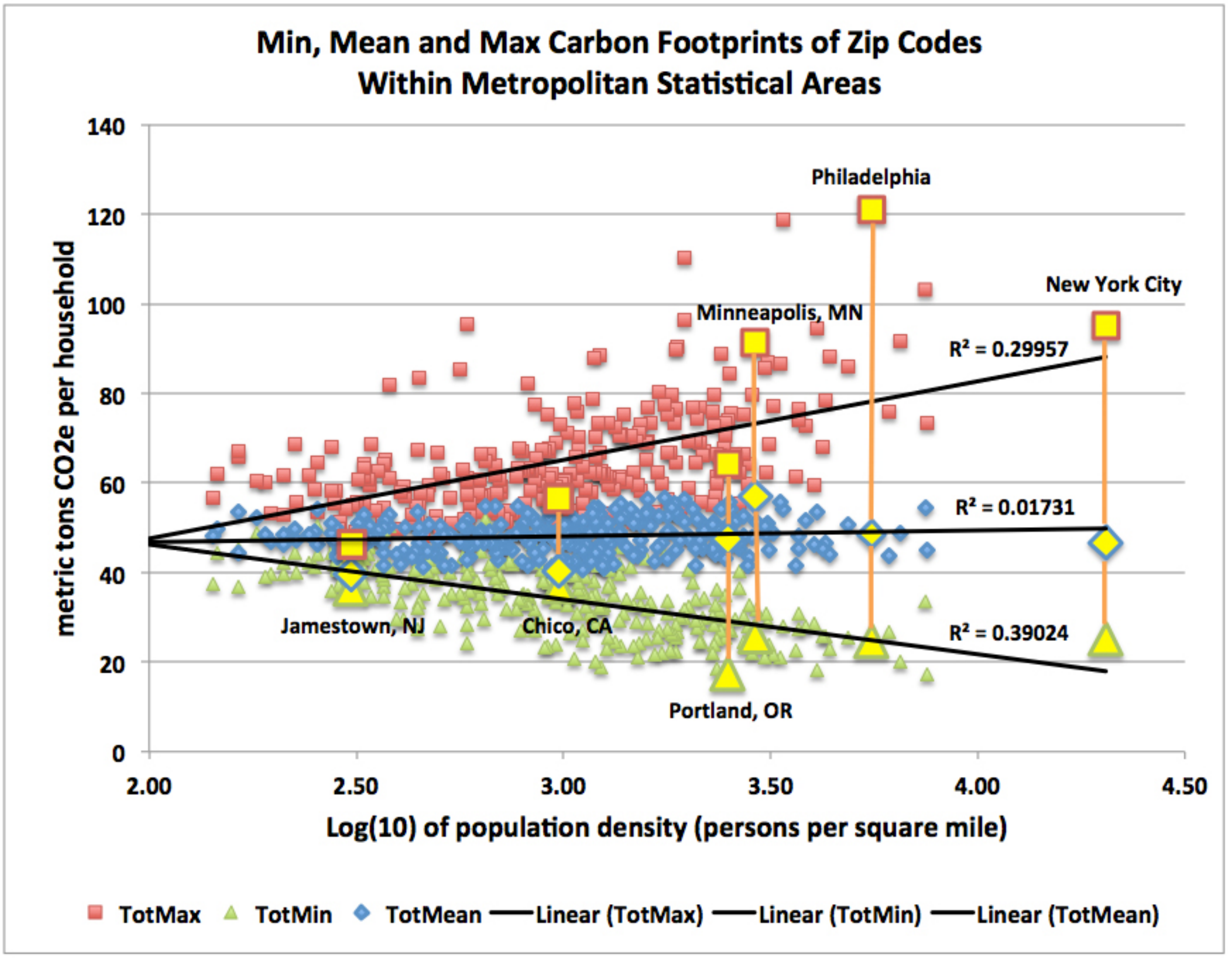


Figure 19. Min, mean and max carbon footprints of zip codes within metropolitan statistical areas, ordered by log of population density (x-axis)

Table 18. Household carbon footprints in metropolitan statistical area principal cities, suburbs and rural & micropolitan areas.

	Trans	Total	StDev	Pop (M)	Pop den
City, Large	11.3	41.8	8.2	20.3	9,953
City, Mid-size	13.9	45.1	9.5	7.3	3,583
City, Small	14.6	46.6	7.3	13.4	2,117
Rural, Remote	16.0	47.6	5.6	4.4	15
Town, Distant Territory	16.1	48.7	5.1	15.0	160
Suburb, Small Territory	16.8	50.0	6.1	3.3	494
Suburb, Mid-size	17.3	51.0	7.0	5.0	902
Rural, Distant	18.0	51.3	6.1	9.0	74
Suburb, Large	16.9	53.1	8.9	43.9	2,706
Town, Fringe	18.2	53.2	14.7	3.8	251
Town, Remote Territory	18.4	54.5	18.8	1.3	93
Rural, Fringe	19.1	55.8	7.8	12.9	254

Table 19. Household carbon footprints in metropolitan statistical area principal cities, suburbs and rural & micropolitan areas

	Pop (M)	tCO2/cap	tCO2/hh	MtCO2	%
Metropolitan Areas	241	18.4	49	4,442	80%
principal cities	98	17.2	44	1,695	30%
suburban	143	19.3	53	2,747	49%
Rural & Micropolitan	59	19.5	50	1,145	20%
TOTAL	300	18.6	49	5,588	100%

Analysis of all urban cores (also called principal cities), suburbs and rural areas is presented in Tables 18 and 19. Large, population dense cities, which are defined as urbanized areas inside a principal city (Ingram and Franco 2012) have lower HCF than smaller principal cities; however, the opposite is true with large, relatively population dense suburbs, which have higher HCF than smaller suburbs. We find no evidence that increased population density correlates directly with lower household carbon footprints in suburbs or rural areas; in fact, the opposite appears to be true. Transportation carbon footprints are about 50% higher in large suburbs compared to large principal cities, while total carbon footprints are about 25% higher, or 10 tCO_2e. Table 19 summarizes results from all U.S. zip codes, including 300M people, or over 99.6% of total U.S. population in the model year of 2007. Metropolitan statistical areas account for about 80% of the U.S. population and household carbon footprints. Principal cities, as defined by the U.S. Census, account for about 30% of U.S. carbon footprints, while locations outside of principal cities but still within metropolitan areas (suburbs), account for about 50% of total U.S. household contributions to climate change. Total HCF for all U.S. locations is nearly 6 billion metric tons of CO_2 equivalent, or about 80% of total U.S. GHG emissions, but would likely be equivalent to nearly 100% of total U.S. GHG emissions if the carbon intensity of imports were considered (Weber and Matthews 2008). Our estimate aligns very closely with other national HCF studies of the United States (Hertwich and Peters 2009; Jones and Kammen 2011; Weber and Matthews

2008), all of which estimate average U.S. HCF at about 50 tCO_2e. Future versions of this work would benefit from inclusion of a multi-regional input-output model to account for the carbon intensity of international supply chains (Weber and Matthews 2008).

In order to develop the best explanatory model of the results we regressed total HCF against independent variables for each zip code in the dataset (Table 20). Of the 37 independent variables included in the regression models, 6 variables explain 92.5% of the variability for all zip codes, 96.2% in principal core cities and 94.6% in suburbs, as measured by adjusted r-squared. In order of their influence on HCF, controlling for all variables entered previously (or stepwise) these are: number of vehicles per household, annual household income, carbon intensity of electricity, number of rooms (a proxy for home size, which is not available for zip codes), natural log of persons in household and log of population density (model 1 in Table 20). The next most significant variables (not shown) are average time to work, fuel prices for gasoline and natural gas, heating degree days and average year homes built; inclusion of these variables improves adjusted r-squared from 0.925 to 0.935. Models 2-4 in Table 20 emphasize the role of population density on household carbon footprints. Consistent with Figure 15, model 2 confirms that is virtually no direct correlation between population density and all zip codes ($\beta = 0.037$, $R^2 = 0.001$) yet there is a reasonably strong correlation when considering only principal cities ($\beta = 0.484$, $R^2=0.234$). Population density also becomes strongly significant when controlling for income and household size ($\beta = -0.3$) for all locations (model 3). When controlling for rooms and number of vehicles, population density is no longer significant due to multicollinearity between population density and these variables (see Supporting Materials for a correlation matrix). Thus, population density appears to affect the size of homes and vehicle ownership and these variables in turn affect HCF, along with income, the carbon intensity of electricity, household size, and other factors to a lesser degree. Overall, income is the single largest contributing factor to household carbon footprints, but the combined effect of other model variables, controlling for income, has far greater influence on the model goodness of fit. Income is positively correlated with population density for all locations ($R^2 = 0.339$), but slightly negatively correlated when considering just principal cities ($R^2 =-0.078$).

Table 20. Summary statistics for all zip codes in the dataset (all), principal cities (cores) and suburbs

		all	cores		suburbs	
1	# vehicles	0.338	0.183		0.310	
	annual hh income	0.499	0.476		0.500	
	gCO2/kWh	0.271	0.255		0.288	
	# rooms	0.202	0.242		0.221	
	ln persons per hh	0.179	0.255		0.154	
	log pop. density	-0.126	-0.084		-0.123	
	adj. R-sq	*0.925*	*0.962*		*0.946*	
2	log pop. density	0.037	-0.484		-0.076	
	adj. R-sq	*0.001*	*0.234*		*0.006*	
3	annual hh income	0.754	0.683		0.780	
	ln persons per hh	0.314	0.371		0.266	
	log pop. density	-0.302	-0.320		-0.301	
	year home built	-0.116	-0.060		-0.022	
	adj. R-sq	*0.653*	*0.812*		*0.691*	
4	# rooms	0.448	0.486		0.526	
	# vehicles	0.515	0.472		0.471	
	ln persons per hh	0.008	-0.015	*	-0.014	**
	adj. R-sq	*0.747*	*0.808*		*0.788*	
	N	31,447	3,646		11,011	

Standardized beta coefficients
p <0.001 for all variables, except: *p<0.1, **p<.01
VIF <2.1 for all variables

The diverse composition of household carbon footprints between locations (see Figure 20) is also of significance. Emissions from travel are 3x larger than energy in some locations, while in other locations energy-related emissions are considerably higher than travel. Household energy comprises between 15% and 33% of total household carbon footprints for about 90% of locations, while transportation comprises between 26% and 42%. The carbon footprint of food ranges from 12-20% of total HCF and is in some cases larger than either transportation or energy carbon footprints. Previous research (Jones and Kammen 2011) has further shown that the size and composition of carbon footprints varies even more noticeably for households of different demographic characteristics within locations.

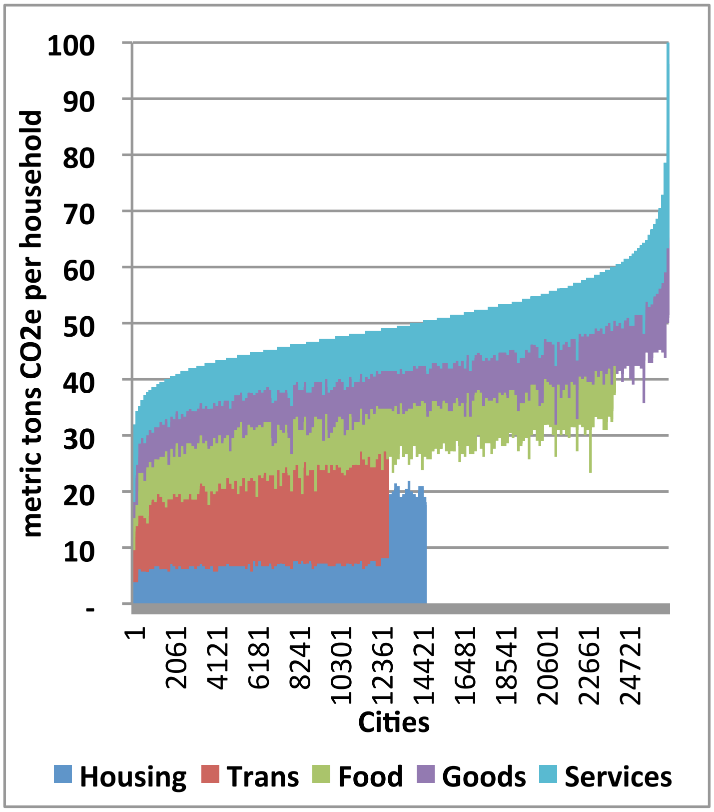


Figure 20. Contribution of housing, transportation, food, goods and services to total household carbon footprints for 26,697 cities, sorted by total

These results should be understood in the context of uncertainty and the methods used to derive the estimates. We have used national survey data to predict consumption at fine geographic scales and have used average GHG emission factors to estimate emissions. This approach hides important regional differences. For example, while we estimated vehicle miles traveled for every zip code in the U.S. using locally-available data, we have assumed average vehicle fuel economy for all locations. We have also assumed similar diets, housing construction, water and waste-related emissions due to lack of regionally specific data. Some of the model variables may indicate multiple conflicting aspects of urban form. For example, increased travel time may simultaneously indicate increased traffic, higher use of public transit and longer travel distances. Also, population density does not account for mixed use, such as commercial and industrial zones co-located in populated areas. Additionally, as noted under model validation in the Supporting Materials, the model tends to underestimate emissions for locations with relatively high consumption.

Uncertainty

These results should be understood in the context of uncertainty and the methods used to derive the estimates. We have used national survey data to predict consumption at fine geographic

scales and have used average GHG emission factors to estimate emissions. This approach hides important regional differences. For example, while we estimated vehicle miles traveled for every zip code in the U.S. using locally-available data, we have assumed average vehicle fuel economy for all locations. We have also assumed similar diets, housing construction, water and waste-related emissions due to lack of regionally specific data. The results should be considered benchmarks by which more accurate local assessments may be compared; such an analysis would be akin to determining level of efficiency compared to what might be expected from similar U.S. locations. The model shows expected consumption given the variables known at the level of zip codes. Local energy policies are reflected in the model only to a certain degree, by inclusion of some states as dummy variables.

The results from this analysis suggest sharp differences between urban and suburban households. The model likely understates these differences as it does not consider differences in motor vehicle fuel efficiency, which is likely higher in city centers that require smaller vehicles. City centers have also been shown to be more politically liberal and more likely to support climate change policy, including fuel-efficient vehicles, as well as other energy efficiency measures that are not captured in this model. Also, as noted under model validation above, the model tends to underestimate emissions for locations with relatively high consumption.

The primary purpose of our paper is not to highlight which model variables have the strongest impact on HCF, particularly since we have been selective about which variables to include (i.e., only those available at the zip code level). Rather, the purpose is to build the strongest model possible to predict energy consumption, VMT, consumption, etc, at fine geographic resolution. As a result of multicollinearity between several variables in our consumption models variables should not be ranked based on the relative importance.

In Table 20, on the other hand, we have attempted to explain relative contribution of independent variables on our results. For this purpose we created a single table of results from our regression models of energy, motor vehicles and consumption, in addition to the most important independent variables used in those models, for every zip code. We then created several multivariate linear regression models of these results in order to analyze the relative contribution of independent variables. We ran these models for the entire dataset of zip codes as well as for subsets of the data for principal cities (urban cores) and suburbs. Unlike our regression models of energy, transportation and consumption, for which prediction was the objective and collinearity was therefore not a relevant concern, the objective of this analysis was interpretation of causation so understanding of collinearity was essential. Coefficient correlations matrices and estimate of variance inflation factors is included in Table 21. The variance inflation factors (VIF) of independent variables for the full model and suburbs were never greater than 2.0 in the full model, and 3.2 when just considering principal cities. We chose models 2, 3 and 4 in Table 20 in the to highlight the effect of colinearity, in particular the effects of population density and income. First, population density becomes not only a significant variable, controlling for all others, but it also becomes strongly correlated with rooms per household (a proxy for home size) and vehicles per household. The correlation between population density and income also becomes strongly negative, whereas in the full model the correlation is only slightly positive (i.e., relatively dense suburbs are richer and relatively dense principal cities are poorer). Entering variables in stepwise fashion was also helpful to understand interaction between variables. The variable with the strongest correlation with total CO_2 per household is number of vehicles per household. When controlling for income, the standardized beta coefficient decreases from 0.789 to 0.613 and further decreases to 0.338 (lower than the beta coefficient of income = 0.499) when controlling for all 5 other independent variables included the full model. Income correlates positively with population density when considering all zip codes, but slightly negatively when only considering zip codes in principal cities. VIF for all variables is under 2.0 for the full dataset, less than 3.2 for cores and less than 2.4 for suburbs. VIF near 3 indicates some collinearity, as is apparent in the correlation matrices; however, the level of collinearity is not severe enough to warrant excluding any variables from the model. As a rule of thumb collinearity is considered severe if VIF is over 10, and even then may not require excluding variables from the model (O'brien 2007).

Table 21. Pearson's coefficient correlations matrices of results presented in Model 1 and VIF

All

	Total	# vehicles	annual hh income	gCO2/kWh	# rooms	log persons per hh	log pop. density	VIF
Total	1.00	0.79	0.69	0.30	0.76	0.42	(0.04)	
# vehicles	0.79	1.00	0.39	0.21	0.61	0.37	(0.07)	1.88
annual hh income	0.69	0.39	1.00	(0.17)	0.55	0.18	0.34	1.87
gCO2/kWh	0.30	0.21	(0.17)	1.00	0.12	0.07	(0.21)	1.19
# rooms	0.76	0.61	0.55	0.12	1.00	0.25	(0.02)	2.03
log persons per hh	0.42	0.37	0.18	(0.07)	0.25	1.00	0.03	1.19
log pop. density	(0.04)	(0.07)	0.34	(0.21)	(0.02)	0.03	1.00	1.24

Cores

	Total	# vehicles	annual hh income	gCO2/kWh	# rooms	log persons per hh	log pop. density	VIF
Total	1.00	0.84	0.75	0.35	0.84	0.47	(0.48)	
# vehicles	0.84	1.00	0.56	0.21	0.73	0.43	(0.56)	3.21
annual hh income	0.75	0.56	1.00	(0.01)	0.56	0.09	(0.19)	1.85
gCO2/kWh	0.35	0.21	(0.01)	1.00	0.22	(0.06)	(0.24)	1.17
# rooms	0.84	0.73	0.56	0.22	1.00	0.41	(0.42)	2.56
log persons per hh	0.47	0.43	0.09	(0.06)	0.41	1.00	(0.17)	1.46
log pop. density	(0.48)	0.56	(0.19)	(0.24)	(0.42)	(0.17)	1.00	1.55

Suburbs

	Total	# vehicles	annual hh income	gCO2/kWh	# rooms	log persons per hh	log pop. density	VIF
Total	1.00	0.78	0.73	0.33	0.80	0.38	(0.08)	
# vehicles	0.78	1.00	0.42	0.19	0.58	0.39	(0.14)	1.84
annual hh income	0.73	0.42	1.00	(0.12)	0.67	0.15	0.29	2.29
gCO2/kWh	0.33	0.19	(0.12)	1.00	0.11	(0.05)	(0.19)	1.15
# rooms	0.80	0.58	0.67	0.11	1.00	0.21	0.00	2.38
log persons per hh	0.38	0.39	0.15	(0.05)	0.21	1.00	(0.01)	1.20
log pop. density	(0.08)	(0.14)	0.29	(0.19)	0.00	(0.01)	1.00	1.20

Quantification of uncertainty for the current dataset was not possible. While sampling error is available in national household surveys, including only this form of uncertainty would be misleading since many other sources of uncertainty exist, including measurement error, aggregation error associated with deriving average emission factors, model errors associated with using a limited number of variables, and other sources of error. The current paper draws limited conclusions that are strongly represented by the dataset and should not be greatly affected by uncertainty.

4.4. Discussion

In this study we characterize average household carbon footprints of essentially all populated U.S. locations and reveal a new relationship between population density and household carbon footprints. In contrast to other research using much smaller datasets we find no direct correlation between population density and HCF when considering all U.S. locations (r-squared < 0.001 for zip codes and cities). Furthermore, we find that the mean, variance and range of emissions actually increases until a population density of about 3,000 persons per square mile is reached, after which mean HCF declines logarithmically, leveling out at a lower limit of about 30 tCO_2 per household (35% below average) at densities over 50,000 persons per square mile. On average, household carbon footprints are 25% higher in suburbs compared to urban cores, yet it is the combined effect of urban cores and suburbs that define the contribution of metropolitan areas. The largest metropolises contain zip codes in the centers of urban cores that have roughly 50% lower household carbon footprints than average, as well as outlying suburbs that are roughly 2 time higher than average, a factor of 4 difference. In contrast, the difference between lowest and highest HCF of zip codes in small metropolitan areas is only 1.5x. The combined net effect of HCF in urban cores and suburbs is slightly higher average HCF in larger metropolitan areas.

The inverted U shape relationship between population density and household carbon footprints suggests the following relationship. Urbanization increases wealth, consumption and emissions. When population density reaches a threshold of about 3,000 persons per square mile, the mean, range and variance of household carbon footprints in urban cores decline due largely to smaller homes, lower gasoline consumption and also somewhat lower incomes. At the same time, carbon footprints and population in suburbs increase. The net effect of larger, more population dense metropolitan areas is a small increase in household contributions to climate change. The two largest metropolitan areas, New York and Los Angeles, are exceptions with somewhat lower net carbon footprints, suggesting the inverted U relationship may hold for extremely population-dense metropolitan areas, or megacities. Similar comprehensive studies in other countries are needed to compare the effects of population density and suburbanization to see if lessons in the U.S. are transferable.

[Note: see Chapter 7 for detailed discussion of the following paragraph, which is reprinted here exactly how it was published in Jones and Kammen (2014)]

As a policy measure for suburbs, increasing population density corresponds to higher HCF due largely to income effects. Population density does correlate with lower HCF when controlling for income and household size; however, in practice population density measures may have little control over income of residents. Increasing rents would also likely further contribute to pressures to suburbanize the suburbs, leading to a possible net increase in emissions. As a policy measure for urban cores, any such strategy should consider the larger impact on surrounding areas, not just the residents of population dense communities themselves. Generally, we find no evidence for net GHG benefits of population density in urban cores or suburbs when considering effects on entire metropolitan areas.

Given these apparent limitations of urban planning our data suggests that an entirely new approach of highly tailored, community-scale carbon management is urgently needed. Regions with high energy-related emissions, such as the Midwest, the South and parts of the Northeast, should focus more on reducing household energy consumption than regions with relatively clean sources of energy, such as California. However, if household energy were the sole focus of residential GHG mitigation programs, then between two-thirds and 85% of household carbon footprints would be left unaddressed in most locations; the full carbon footprint of households should be considered in community GHG inventories and management plans. Suburbs, which account for 50% of total U.S. HCF, tend to have high motor vehicle emissions, large homes and high incomes. These locations are ideal candidates for a combination of energy efficient technologies, including whole home energy upgrades, solar photovoltaic systems and electric vehicles. Food tends to be a much larger share of emissions in urban cores, where transportation and energy emissions tend to be lower, and in rural areas, where household size tends to be higher and consumption relatively low.

Several recent studies for California (Long et al. 2011; Wei et al. 2013; Williams et al. 2012) conclude that 80% reductions are possible only with near technical potential efficiencies in transportation, buildings, industry and agriculture. To the extent that these efficiencies are not met, highly tailored behavior-based programs must make up the difference to decrease demand for energy, transportation, goods and services that drive emissions.

ASSOCIATED CONTENT

Carbon footprints profiles of all U.S. zip codes, cities, counties and states are available on the project website: http://coolclimate.berkeley.edu/carboncalculator and an interactive mapping website: http://coolclimate.berkeley.edu/maps.

Chapter 5: Information Strategies to Enable Behavior Change

Consumer demand for goods and services drives global economic activity and associated environmental impacts. Policies addressing consumption have overwhelmingly focused on increasing efficiency, producing less pollution and greenhouse gases for the same amount of work (Fuchs and Lorek 2005). Yet reducing consumption directly has immediate benefits. Industrialized countries with the relatively low per capita GHG emissions also have lower rates of household consumption and motor vehicle usage (Hertwich and Peters 2009). There are two primary mechanisms to address household consumption via policy. First, urban planning holds potential to influence household behavior by making it easier to live more sustainable lifestyles. Chapter four highlights the importance of the home size and location as perhaps the two most critical factors driving household consumption. The second approach is to engage individuals and households directly, in their existing environments, through behavior change interventions. This chapter reviews theory relevant to designing effective behavior campaigns. Chapter six presents a pilot program designed to scale up the adoption of low carbon technologies and practices in California cities.

5.1. Relevant theories of behavior

All major branches of social science (anthropology, economics, political science, psychology and sociology) contribute important theoretical frameworks toward understanding and influencing human behavior. Early behavioral theories were heavily grounded in economics and the "rational choice model." Rational choice states that individuals calculate the costs and benefits of different choices and choose the option with the highest expected net benefits. The assumption is that consumers make optimal choices except in the presence of market barriers or market failures, which are well known in economics literature. Typical barriers preventing energy efficient behavior include information barriers (e.g., lack of perfect knowledge of present and future energy costs), split or misplaced incentives (e.g., when landlords own equipment and tenants pay energy bills), lack of financing options, regulator barriers (e.g., when pricing does not reflect the true cost of energy), and "gold plating," (when efficiency is bundled with other high cost options consumers don't need) (Blumstein et al. 1980; Golove and Eto 1996). Simon (1972) elaborated the concept of "bounded rationality" to account for the inability of individuals and organizations to fully account for risks and uncertainty given complex and imperfect information. Behavioral economists, drawing largely on work in experimental psychology, have pointed to other psychological processes that inhibit or influence rational decision-making. They suggest that a better understanding of psychology will help economists understand decision making "on their own terms" without rejecting the principles of neoclassical economics (Camerer, Loewenstein, and Rabin 2011).

Approaches in psychology and sociology have tended to eschew the rational actor model in favor of psychological and social processes that do not have utility maximization as the fundamental goal of decision-making. Social psychologists emphasize the importance of other people's attitudes on individual decision-making. Ajzen and Fishbein's Theory of Reasoned Action (TRA) was the first to emphasize the importance of intention as the precursor to behavior. If an individual has a strong intention to do something they are much more likely to take that action. Intention is mediated by an individual's attitudes toward the behavior and their beliefs about what others may think of their actions (a subjective norm). Azjen's highly influential Theory of

Planned Behavior (TPB) (Ajzen 1991) extends this model by including a third factor influencing intention and also behaviors directly: perceived behavioral control, or the extent to which an individual believes s/he has the requisite skills, time, money, cooperation of others and general ability to conduct the behavior. Perceived behavioral control is quite closely related to Bandura's (1977) concept of perceived self-efficacy, or individual's belief in how well they are able to carry out particular actions. TPB has been widely applied to influence a wide range of behaviors, including alcohol, smoking, health tests, food choice, accident avoidance, collective action and promoting sustainable behavior (Jackson 2004).

A second strand of theory extends the concept of attitudes with an emphasis on how values shape attitudes and ultimately personal norms toward given behaviors. In contrast to TPB, Schwartz (1977) argues that people often take behaviors to benefit others based on their personal values, regardless of what others may think of their actions. Schwartz contends that personal norms of behavior are the consequence of individuals' awareness of consequences and ascription of responsibility. This theory was extended in Paul Stern's Value Belief Norm Theory (Stern 2000) which postulates that positive correlation with biospheric values and negative correlation with egoistic values are conditions for pro-environmental behavior. In practices, however, pro-environmental norms exhibit only a weak correlation with pro-environmental behavior (Jackson 2004) as does intention. In a recent meta-analysis of 57 studies, intention explained only 27% of variance in pro-environmental behavior (Bamberg and Möser 2007).

A somewhat less well-known theory, Triandis' Theory of Interpersonal Behavior (Triandis 1979), extends the previous models mentioned to include habit and affect (i.e., emotional responses). Habits have been shown to have a large influence on behavior. For example, the Transtheoretical Model of Behavior Change (Prochaska 2013) contends that behaviors are sustained only after an individual has gone through a process of contemplating, preparing, conducting, and maintaining actions. Habituated actions therefore do not require intentions, but act directly on behaviors. Triandis also includes emotive aspects of decision-making, e.g., when emotional appeals of advertising or product design influence product choice. Triandis's theory has been shown to have more predictive power then the Theory of Planned Behavior (Bamberg and Möser 2007), but perhaps due to its complexity it has had less influence in the literature and in practice.

In sum, a larger number of processes affect individual and collective behavior, including the influence of peers, values, attitudes, strength of habits, affect, perceived behavioral control, actual control (e.g., due to environmental conditions) and cognitive processes. Given this complexity, scholars and practitioners of social marketing often rely on segmentation to target behaviors to particular groups of individuals. One such study conducted by Opinion Dynamics for the California Public Utilities Commission (Opinion Dynamics 2009) conducted to characterize Californians' potential uptake of energy efficiency measures. Using a statewide survey and statistical analysis to measure attitudes and behaviors the authors segmented the California population into five distinct groups. "Leading Achievers," accounting for 22% of Californians, have strong environmental attitudes and have taken a number of important energy efficiency measures. They tend to by highly educated, politically liberal, older and wealthier than other segments. "Practical Spenders," (18%) have also taken a number of efficiency measures but they are primarily concerned about making smart economic decisions and are not motivated by environmental appeals. They tend to be older, more politically conservative and somewhat less educated. “Striving believers” (25%) are highly motivated by environmental appeals, but are younger, tend to be renters and have not yet engaged in large energy efficiency measures like their older “Achiever” counterparts. Other Californians are either “Thrifty Conservers” (21%) or “Disconnected” (15%) and are not ideal candidates for energy efficiency campaigns.

Community-Based Social Marketing (CBSM) extends the importance of audience segmentation by targeting specific actions to specific localized population segments. CBMS, as elaborated by Doug McKenzie-Mohr (McKenzie-Mohr 2013) is a five step process: 1) choose actions with the most potential to meet objectives for target audience, 2) identify barriers and benefits of taking the action for the specific population, 3) use behavior change “tools” to overcome barriers and highlight benefits, 4) pilot test the intervention, and 5) scale up the intervention to the entire population. CBMS has been widely implemented as best practices in a range of contexts, including health and environmental campaigns. Many of the “tools” used in CBMS are discussed below in the context of an energy-reduction competition.

5.2. The promise of competitions

Chapter six of this dissertation presents an inter-community energy and carbon footprint reduction competition that was designed, implemented and evaluated as part of this research. The competition design draws on a number of relevant behavioral theories and practices common to community-based programs seeking to encourage adoption of pro-environmental practices. This section presents some of the key behavioral concepts as well as results from a preliminary review of 20 energy reduction competitions, currently in preparation (Jones and Vine 2014).

Previous studies have highlighted the effectiveness of competitions to motivate more sustainable behavior, particularly when combined with other intervention strategies, such as providing tailored information, encouraging commitments and goal setting, modeling of normative behavior, providing personal and comparative feedback and offering rewards like recognition and prizes (Petersen et al. 2007). Competition between groups fosters in-group collaboration, proving social motivations, and complementing intrinsic motivations for pro-social and pro-environmental behavior. Individuals’ values, habits, abilities, attitudes, social ties and worldviews are also among the factors that influence behavior (Stern 2000). Competitions are thought to be particularly effective at engaging otherwise hard to reach populations (McKenzie-Mohr and Schultz 2014) and not just the lowest energy users, who themselves have diverse reasons for engagement in energy conservation (Deumling, Meier, and Cook 2013). Energy and carbon footprint savings frequently result in average short-term savings 5-20% (Abrahamse et al. 2005) and can lock in longer-term savings through purchase of new energy efficient equipment and habit formation (Maréchal 2010).

Comparative feedback, providing normative information on the energy usage, goal achievement or performance of peers, may be the most essential theoretical construct underlying energy reduction competitions. Comparative feedback has received considerable attention in the literature, as well as in practice. Shultz et al. (2007) demonstrated the effectiveness of neighborhood comparisons to reduce household energy consumption. When combined with an injunctive normative message of approval (e.g., a smiley face) or disapproval, neighbor comparisons result in consistent energy reductions. Recent studies comparing home energy reports in numerous randomized field trials demonstrate savings of 1-2% (Allcott 2011; Ayres, Raseman, and Shih 2012), with higher savings for high consuming households (Allcott 2011) and political liberals (Costa and Kahn 2013). Home energy reports showing comparative feedback have grown into a billion dollar business, with companies like Opower providing reports to millions of residential energy consumers in the United States, and increasingly abroad. Energy reduction competitions typically show rankings of individual households, groups, office floors, buildings or other comparisons and encourage and reward participants for moving up in the rankings. In a recent meta-analysis of 156 information-based experiments (Delmas, Fischlein, and Asensio 2013), comparative feedback had the second highest average energy savings (11.5%) of strategies considered, after energy audits (13.5%), which tend to be considerably more costly and "high touch."

Descriptive and injunctive norms may further be applied in messaging strategies directly with participants. The power of norms to influence behavior has been known for many decades. In one famous study showing descriptive norms Milgram, Bickman and Berkowitz (1969) asked a crowd of people to stand on a street corner and look up at an empty spot on a building; the more people in the crowd, the more likely other people were to stop and look up. This may be an adaptive behavior that acts as a shortcut to reduce decision-making; by merely observing and imitating others we are likely to make reasonable decisions in less time. Environmental campaigns should take care to use descriptive norms appropriately. If most people behave in a non-environmental way, pointing this out may lead to less environmentally-friendly behavior (Cialdini 2003). Instead, according to the Focus Theory of Normative Conduct by Cialdini and colleagues (Cialdini, Reno, and Kallgren 1990), in these cases it is better to focus on what is socially acceptable behavior, or an injunctive norm. This was demonstrated elegantly in a pilot study at a petrified national forest where signage previously indicated that every day wood was stolen from the forest, totalling 14 tons per year. When signage was changed to a strong injunctive message ("if even one person steals, it undermines the integrity of the forest"), pillage was reduced by 80% (Cialdini et al. 2006).

Normative messaging and other persuasive messaging techniques (Goldstein, Martin, and Cialdini 2008) may be most influential when the messenger is trusted and credible (Fuller 2011). In most cases this means messages should come from someone that is known to participants locally, a central tenet of community-based social marketing (CBSM) (McKenzie-Mohr 2013). Under CBSM, community members are in the best position to develop meaningful strategies to overcome barriers and highlight the benefits of taking particular actions. Local messengers may also use more effective language based on shared values, history and motivations. Messaging may also be more effective through the use of local images or stories, particularly if they tap into shared cores values, which evokes an emotive response (Schwartz 1994).

Inter-community energy or GHG reduction competitions have not been systematically studied, and only a few have been conducted to date (Jones and Vine 2014), but several aspects of cities make them seemingly amenable to such an intervention. Cities are nexuses of social ties and social networks, which can help increase participation in pro-environmental programs through social diffusion (McKenzie-Mohr). Cities may also be particularly effective at disseminating environmental messages and behaviors if people feel an emotional, cognitive or functional bond with their community, or place attachment (Halpenny 2010). Perhaps the most highly visible placed based attachment is when residents rally around a local sports team, particularly when there are rivalries with other communities. Building on this notion, the Kansas Take Charge Challenge, an energy reduction competition between small Kansas communities, chose tows within the same football conferences to compete (Barnett 2010). People may also feel more strongly connected to local institutions, such as schools, churches and social groups, which may be mobilized or formed into teams in a community-based energy challenge.

Inter-community energy and GHG reduction campaigns have several advantages that make them suitable for community-based pro-environmental campaigns. First, they tend to appeal to a wider cross-section of the population than purely environmentally-focused campaigns (McKenzie-Mohr and Schultz 2014). This enables them to reach a larger scale within communities while also engaging multiple communities at once. Second, the comparative feedback provided to participants may be much more visceral than reports showing generic neighbors, since participants are often ranked against their peers. Finally, gamification aspects, with participants completing actions and reaching intermediate goals, may enhance enjoyment and sense of achievement and positive feedback (Brewer, Lee, and Johnson 2011).

A recent review of twenty energy reduction competitions (Jones and Vine 2014) demonstrates that most such programs utilize a number of complimentary behavior change strategies. Figure 21 shows the prevalence of behavior changes tools or strategies in each program. Green and a value of 2 indicates clear, explicit implementation of the strategy, while yellow and a value of 1, indicates a seemingly relatively weak implementation of the strategy, or if the strategy was not a central focus of the program. The most common approaches, in order of their frequency, were:

1. Local messengers: when messaging about the program comes from someone they know or someone local,
2. Comparative feedback: information on performance of individuals or groups of individuals is shared among participants,
3. Competition: participants are encouraged to outperform their peers,
4. Incentives: tangible rewards and/or recognition are provided based on performance,
5. Prompts: reminders to complete particular behaviors,
6. Social diffusion: participation increased through use of social networks,
7. Descriptive norms: information on what others like them are doing,
8. Commitments: pledges to take particular actions,
9. Goal setting: targets to achieve
10. Scarcity: when there is a limited supply of something, e.g., an opportunity to earn points.

Other techniques that are used more infrequently include scarcity, reciprocity, tailored feedback, instantaneous feedback, gamification, subjective norms, loss aversion, and coaching.

Project	Local Messengers	Comparative Feedback	Social diffusion	Competition	Imagery	Incentives	Descriptive norms	Prompts	Commitments	Goal setting	Scarcity	Tailored Feedback	Reciprocity	Instantaneous Feedback	Gamification	Subjective norms	Loss aversion	Energy Coach / advisor	# of strategies used
1	2	2	2	2	2	2			2					1					8
2	2	2	2	2	2	2		2	2	2	1		1	2	2				13
3	2	2	2	2	2	2	2	1		1	1		1	2	1	1		1	15
4	2	2	2	2	2	2	2	2	2	2	2	2	1		2	2			15
5	2	1	2	2	2	2	1	2	2	2		1	2			2	1	1	15
6	2	2	2	1	1	1	1	1	2				1						10
7	2	2	2	1	2	2	2	2	2	2	1	1							12
8	2	2	2	1	1	1	1	1			1						1		10
9	1	2	2	2	1	2	2	1			2	1		1	2		2		13
10	2	2	2	1	2	2	1	1	1	1					1				11
11	2	1	2	2		2	2	2		2	1	2	1					2	12
12	2	1	2	2	2	2	2	2	2	2	1	2	2					1	14
13	1	1	2		2	2	2	2	2	1	1	2	1					2	13
14	2		2	1	2	1	2	2	2	2			1			1	2		12
15	2	2		2			2	1	2							2			7
16	2	2	1	2	2		2	1			2	2		2	2	1			12
17	2	2	2	2	2	2	2	2	2	2	1	2	1				2		14
18	2	2		2	2	1		2	2	2			1	2		1		2	12
19	2	2	2	2	2	2	2	2	1	1	2		2	2	2		2	1	16
20		2		1		1	1		1	1									6
Score	36	34	33	32	31	31	29	29	27	23	16	15	15	12	12	10	10	10	18

Figure 21. Presence of common behavior tools in 20 energy reduction competitions

A major lesson of this review was competition is simply one of many strategies that may be used in an energy reduction program. Some competitions have very little emphasis on competition itself, while others made this the central focus. The success of program to change behaviors lies in the effectiveness of the program design and implementation, the capacity of local program managers to execute the program, and the motivations and characteristics of the populations targeted.

A common critique of competitions is that an overemphasis on tangible rewards can reduce intrinsic motivation for individuals to take the desired behaviors and decrease the likelihood that the behaviors will be sustained when the rewards are withdrawn at the end of the competition (Covington and Müeller 2001). This effect can be wholly or partially mitigated by minimizing tangible rewards and by offering positive feedback (Deci, Koestner, and Ryan 1999), which tends to increase intrinsic motivation. Additionally, competition alone, in the absence of external reward, is thought to increase intrinsic motivation, by making the activities more challenging and enjoyable. Evidence also suggests that recidivism after the competition ends depends on the type of reward and the social context in which rewards are offered; if intrinsic motivations are enhanced, the actions will be more likely sustained over time.

Thus, competitions may be helpful in encouraging participation in pro-social and pro-environmental behavior by making taking action more enjoyable, by providing feedback on performance, and by enhancing social interaction among participants. Since individuals did not receive prizes themselves in the Challenge intervention, the focus was on community benefits and recognition for city-wide achievements. Some cities did offer occasional raffle prizes based on points, but these were offered as surprise gifts and were not a central focus of the program. Messaging also focused on intrinsic motivations and utilized a number of behavior strategies, including comparative feedback, normative messaging, peers modeling desired behaviors and other strategies. The combination of these strategies was designed to enhance intrinsic motivation, while competition is used to make participation more meaningful and enjoyable for participants.

Inter-city energy and greenhouse gas reduction competitions have only recently been tried (e.g., Mass Saves Challenge, the Kansas Energy Challenge). Previous programs have not been rigorously evaluated and little is known about why programs may or may not be successful. This study provides one of the first opportunities to evaluate a statewide inter-city greenhouse gas reduction competition. Given the novelty of this program, this study serves as a case study to improve understanding of similar efforts. The program is intended to demonstrate the ability of local communities to utilize behavior change practices to engage residents successfully in reducing household carbon footprints at scale. While this is only a pilot program (now in its second year), it may serve as a proof of concept to scale up future program efforts to engage a wider cross-section of California residents in voluntary greenhouse gas reductions.

Chapter 6: The CoolCalifornia Challenge: Using Inter-City Competition to Foster Community-wide Climate Engagement

6.1. Introduction

The goals of this project were to design, implement and evaluate a carbon footprint reduction program for California households and communities. The program, called the CoolCalifornia Challenge (or simply the "Challenge"), used inter-city competition and community-based social marketing strategies to motivate residents in participating California cities to understand, track and reduce household greenhouse gas emissions.

A number of recent studies (Long et al. 2011; Williams et al. 2012; Wei et al. 2013) have concluded that large scale adoption of energy efficient and low carbon technologies will be required for California to meet its 80% GHG reduction target (Executive Order S-3-05). These studies further show that even if low carbon technologies can be scaled up to near technical potential, additional savings will be required from conservation, or else entirely new technologies will need to be developed, likely at considerable cost. Unlike changes in technology and infrastructure, which require heavy investments and long lead times, behavior change programs can offer quick and potentially low-cost solutions (Dietz et al. 2009).

Efforts to encourage pro-environmental behaviors have been largely limited to small-scale projects that target actions for specific populations (McKenzie-Mohr 2013). One approach, providing comparative feedback via home energy reports, has reached large scales; however, savings have been modest, typically between 1-2% (Ayres, Raseman, and Shih 2012; Allcott 2011). Low-cost, highly scalable intervention models that achieve deeper savings for large, diverse populations are needed to ramp up greenhouse gas reductions.

This study developed a pilot inter-city greenhouse gas reduction program between eight participating California cities. This project serves as a living laboratory to test new approaches to engage California residents and communities in climate action. This effort supports the goals of the California Global Warming Solutions Act (AB 32); as specified in the California Air Resources Board's AB 32 Scoping Plan, voluntary actions are an essential component of the state's GHG reduction portfolio.

The primary goals of this study were to: 1) design and implement a pilot inter-city greenhouse gas reduction competitions between California cities, 2) administer a research survey to collect participant demographic information, attitudes, motivations, adoption of low carbon behaviors and other information, and 3) track and evaluate results.

The study tracked self-reported monthly natural gas and electricity consumption by ~900 total participants who recorded their monthly usage an average of five months per household. We use a quasi-experimental design to compare participants' monthly energy usage with participants who joined the program at a later date and estimated total program-wide savings of electricity, natural gas and greenhouse gas emissions.

Participants were asked to complete a research survey, including questions on their values, attitudes, motivations, commitment to sustainable lifestyles, and demographic characteristics. In order to understand the effectiveness of the program to engage different population segments we compared points earned by households to responses from the research survey. As described in detail below, participants earned points earned for: 1) having lower energy consumption and motor vehicle usage than similar California households, 2) lowering energy usage and motor vehicle usage over time, and 3) taking simple, one-time actions.

6.2. Methods and Materials

6.2.1. Program Overview

Any California city interested in the program was encouraged to apply and participate. Applications were accepted from February 1, 2012 through February 29, 2012. Interested cities were required to submit a letter of support from a city manager or equivalent stating the city's commitment to participate in the program. The first six cities that submitted letters of support signed by city managers received $1,000 in seed money. The city had the option of designating a community-based organization (CBO) to administer the program. If a CBO was in charge of administering the program locally, a letter of support from this organization was also required.

The California Air Resources Board, U.C. Berkeley and CoolCalifornia.org partner, Next Ten, announced the program and advertised on institutional email lists and a list of city sustainability officers throughout the state. Ten cities completed the application process by the required date; however, two cities, Gonzales and Santa Cruz, dropped out prior to the start of the competition due to staffing constraints, leaving eight cities in the pilot competition:

- Chula Vista
- Citrus Heights
- Davis
- Pittsburg
- Pleasanton
- San Jose
- Sacramento
- Tracy

Theses cities reflected a demographically diverse population with a range of population sizes as well as different levels of capacity and experience with community climate action. All cities had recently completed climate action plans that called for some level of engagement with residents. In many cases the Challenge was the city’s first engagement with residents on this issue.

The CoolCalifornia Challenge (“the Challenge”) management team at U.C. Berkeley worked directly with city program managers in each city, providing supporting resources, including: 1) marketing information (brochures, videos, market segmentation research, graphically-enhanced email communication, etc.), 2) survey results (in aggregated form), 3) a calendar of monthly themes and suggested activities, 4) community-based social marketing workshops (online during the Qualifying Round and in-person and online during Finalists Round), and day-to-day support. Other resources were contributed by cities depending on their needs and capabilities, including staff and volunteer time, print materials, coordination of local events, communication with participants via the Challenge software and local program management.

6.2.1.1. Target Population

Based on a California-focused population segmentation study (Opinion Dynamics 2009) the research team anticipated that two generalized groups would be primarily interested in the Challenge. The first group, called "leading achievers," would be largely well-educated, politically liberal homeowners who are already very knowledgeable and committed to energy efficiency and climate change, and who would be good candidates for large investments and deep conservation practices. The second group, called "striving believers," is younger, more urban and also politically liberal, but due to competing interests, lower incomes and renter status, has not made significant investments in energy efficient technologies. This group is more influenced by peers, highly connected to social media, and more motivated by fun interventions that improve social interactions. Together, these two groups represent nearly 50% of California's population. A third group, called "practical spenders," is older, more conservative and also quite savvy about energy efficiency, but would be less motivated by environmental appeals and not as likely to join the program.

Cities were also encouraged to foster engagement of more specific population segments via the creation of "EcoTeams," or self-organizing groups of participants. EcoTeams could be formed by schools, churches, city offices, community-based organizations or other groups interested in competing against similar teams. EcoTeams would know the best way to communicate with and motivate their more specific populations.

6.3.1.2. Timeline

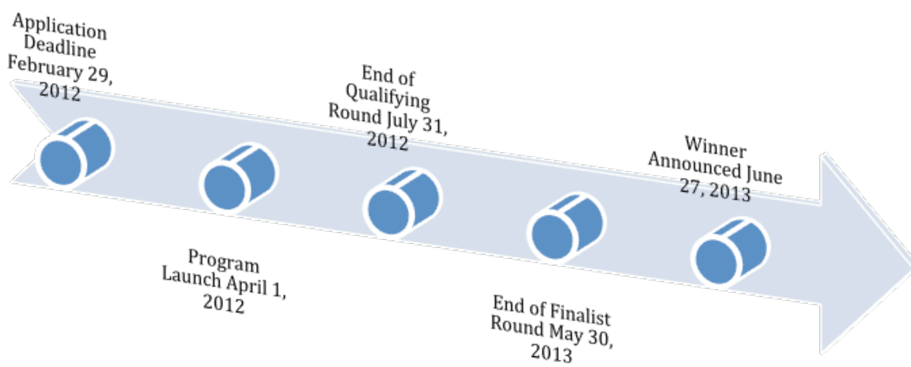


Figure 22. Timeline of the CoolCalifornia Challenge Pilot Competition

The Challenge started on April 1, 2012 and ran through May 30, 2013. The month of April 2012 was called the "**warm up month**," which was designed to give cities the opportunity to become familiar with the software and to start formulating their plans for participation in the Challenge. During this period participants were able to sign up and start earning points in the CoolCalifornia Challenge.

The "**Qualifying Round**," which ran from May 1 through July 31, 2012, was designed to encourage broad participation of California communities in the program and to select the most dedicated cites to compete to become the "Coolest California City." At the end of each month of the Qualifying Round the city with the most points was deemed a "Finalist" and awarded $10,000 in "seed money."

The CoolCalifornia Challenge provided in-kind and financial support to cities participating in the program. The first six cities to apply received $1,000 in seed money. Each winner of the 3-month Qualifying Round was also to receive $10,000. Seven cities in the Pacific Gas & Electric Company (PG&E) territory received additional seed money of $2,500 each from PG&E. The City of Chula Vista was supported separately via contracts with their local utility, San Diego Gas & Electric Company.

The City of Davis became the first finalist at the end of May, followed by the City of Sacramento at the end of June. The remaining cities competed for the last finalist spot during the month of July. The competition between the cities of Tracy and Chula Vista was extremely intense during the final days of the month, with each city trading places on the leaderboard multiple times. By midnight of July 31, both teams had earned almost the same number of points, within less than 0.5%. Both cities agreed to declare a tie and share the prize money ($5,000 each). The cities of Davis and Sacramento also agreed to have an additional city as a finalists, although there was some concern that four cities would spread staff resources and coordination more thinly.

The "**Finalists Round**" ran from August 1, 2012 through April 30, 2013; however, cities were given until May 30 to enter energy bills and vehicle odometer readings for the month of April, resulting in a program ending date of May 30, 2013. The total program duration was 13 months, including the warm up month of April 2012, plus additional month of May 2013 to finish entering data. The program collected more than one year of data since participants were able to enter utility data and vehicle odometer readings dating back to March 1, 2012. The Finalists Round was designed to function similarly to the original competition design, which had three cities collaborating to implement a nine-month program (see Appendix A.5 for a summary of program design changes from the original research contract).

At the end of the one-year pilot, the City of Davis had earned the most points and was officially declared the "Coolest California City" at an awards ceremony at a California Air Resources Board meeting in Sacramento. The city of Chula Vista came in a close second place and the city of Tracy was third place. Chula Vista and Tracy were each awarded recognition as a "Cool California City."

6.2.1.3. Software and Points Structure

U.C. Berkeley developed a sophisticated online software platform (see Appendix A.9 for screenshot) allowing participants to create accounts, log electricity and natural gas bills, add motor vehicles and track odometer readings, join and manage teams, invite friends, share stories, take pledges, track progress and earn points for themselves, their teams and their cities. The software also included administrative accounts for city program managers allowing them to send formatted messages to their participants, administer raffles, and manage Ecoteams.

Developing the software proved to be much more time consuming, costly and complicated than originally envisioned in the research contract, which did not include funding for software development. Rather than try to extensively modify and repurpose an existing software tool developed for the purpose of calculating household carbon footprints (CoolCalifornia.org/calculator), U.C. Berkeley hired a small team of highly skilled computer programming students to build a new website from scratch and hired a fulltime staff person to design and manage the software development. The software launched on April 2, 2012 (a day after the intended start date due to a software bug) with basic functionality allowing users to create accounts, track energy data, earn points and monitor their city's progress on a scoreboard. New features were rolled out over the course of the yearlong program, as the user interface improved and bugs were tracked and resolved on an ongoing basis.

Participants earned points for the following:

1. KUDO POINTS for signing up & taking simple actions: Participants received 100 points for signing up and additional points for simple actions like filling out an online survey (100 points), uploading a photo (50 points), and inviting friends (20 points for every person who signs up).

2. GREEN POINTS for having carbon footprints from home energy and motor vehicles that are lower than similar households: Participants earned one point per pound of CO_2 lower than a benchmark value for similar households. Similar households were defined as having the same

number of people of the same ages living in the same city. Benchmark electricity, natural gas and vehicle miles were calculated for each city and for each household type by number of household members in each age group.

The benchmarking methodology for "similar households" is described in detail in (Jones and Kammen 2014), and summarized here. We use existing national household survey data to develop econometric models of demand for household electricity, natural gas, fuel oil and vehicle miles traveled. Independent variables used to predict household electricity, natural gas and other household heating fuels in the Residential Energy Consumption Survey (n = 4363) include energy prices, heating fuel type, heating and cooling degree days, structure of homes (number of rooms, percent single-detached, year home built), demographic information (income, number of household members, age of householder, race), home ownership, percentage rural or urban, Census divisions, and U.S. state. Predictive variables for motor vehicles miles traveled (VMT) in the National Household Travel Survey (n = 11 744) include number of vehicles owned, fuel prices, average time to work, percentage of commuters who drive to work, demographic information (income, number of household members, race), number of food and recreation establishments in the zip code, population density, Census region, and U.S. state.

Figures 23, 24 and 25 show the benchmark monthly electricity, natural gas and vehicle miles traveled estimates for each of the Challenge cities. Monthly electricity and natural gas estimates were developed using local 30-year average heating and cooling degree days (NCDC 2013). The model somewhat overestimates electricity consumption for California households (likely due to California's stronger energy codes that are not well predicted by the model); however, this only serves to give all Challenge participants more points than they would with a lower benchmark and does not affect the results of this study.

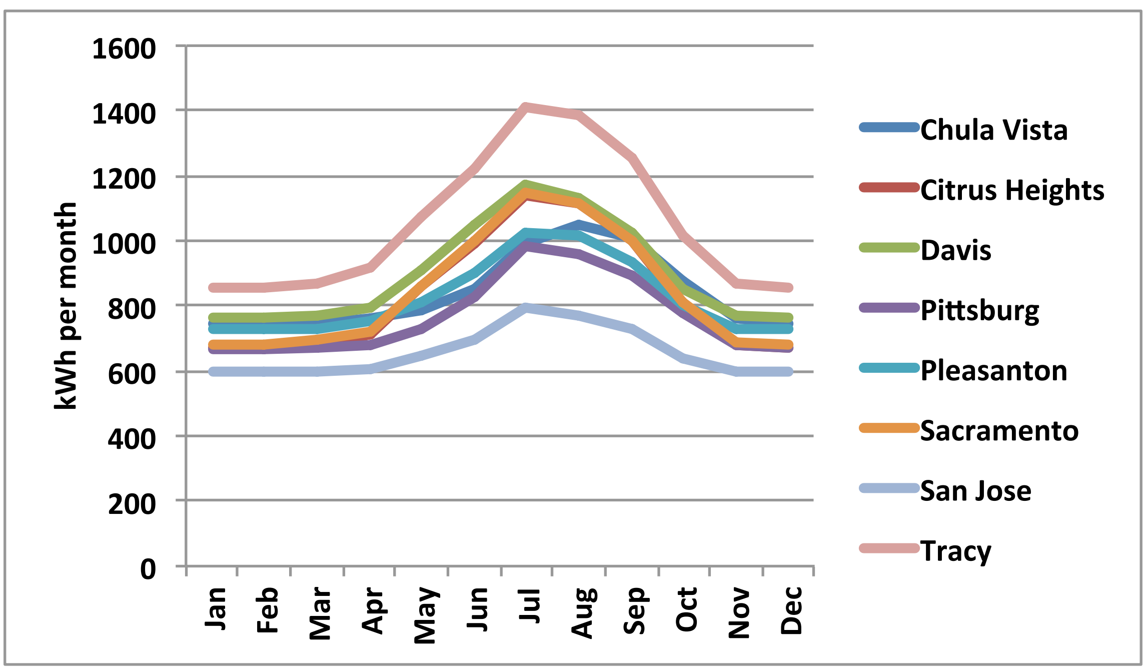


Figure 23. Benchmark kWh Electricity per Household by City

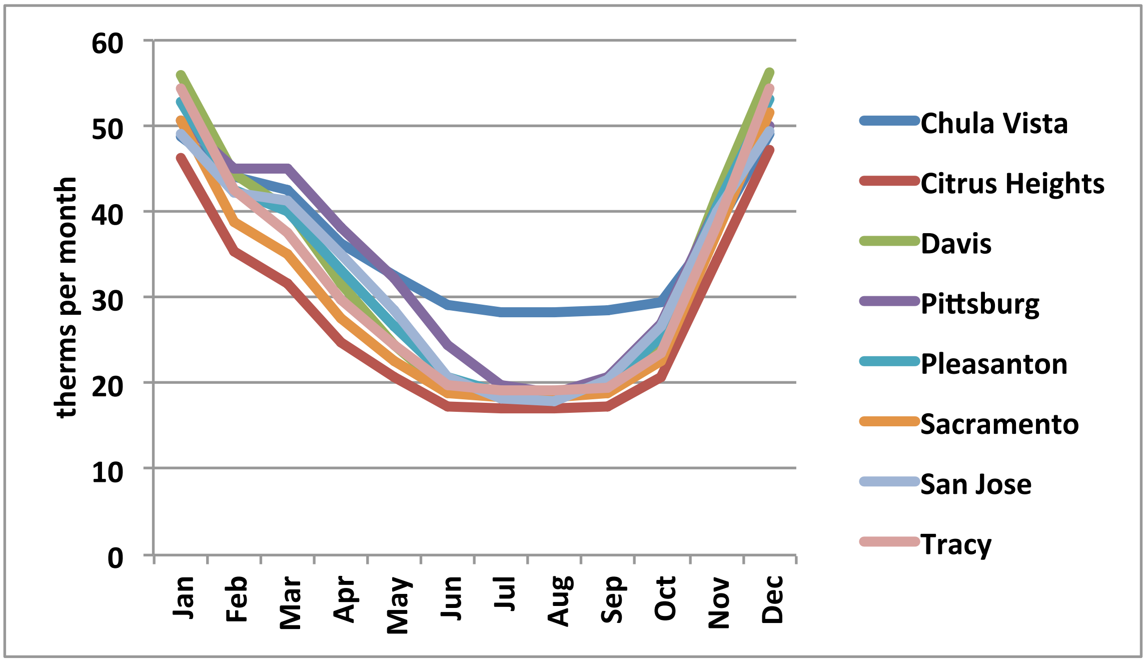


Figure 24. Benchmark Therms Natural Gas per Household by City

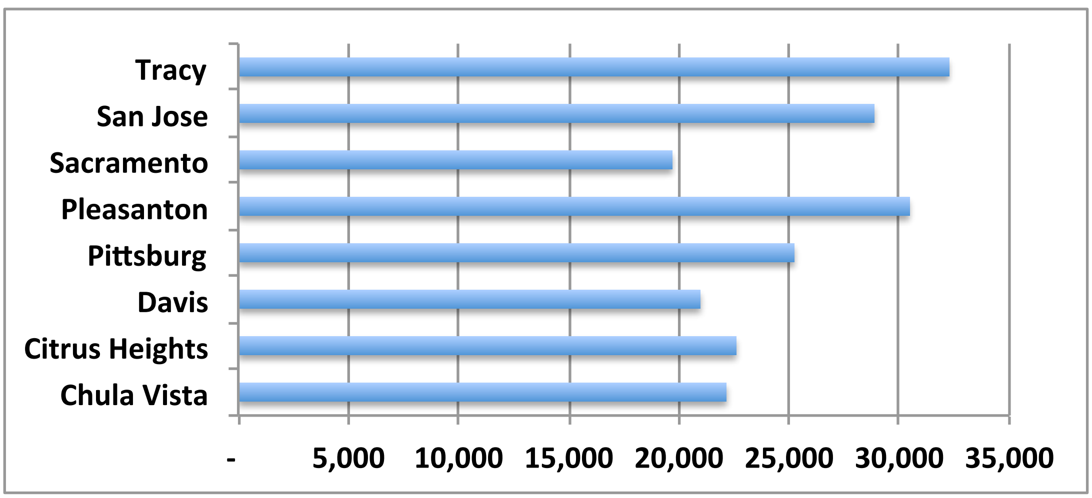


Figure 25. Benchmark Household Vehicle Miles Traveled by City

3. BONUS POINTS for beating past performance: Participants received bonus points for reducing energy and transportation carbon footprints compared to their household's performance in previous months. For example, if a household was 20% below similar households in March and 10% below similar households in April, the software calculates an expected personal benchmark of 15% below for May (the average of previous months). For every pound of CO_2 the household reduced below this personal benchmark they received bonus points equivalent to three times the value of CO_2 saved. These bonus points gave participants additional incentive to lower emissions beyond their reductions in previous months.

6.2.1.4. EcoTeams

During the original program design it was envisioned that most active participants would be organized into teams of 5-7 participants, called EcoTeams. Each EcoTeam would be responsible for enforcing the rules and expectations of the program and verifying the activities of its members. Participants who were not part of EcoTeams would have fewer opportunities to earn points, as agreed upon by a vote of city program managers in participating cities.

Unfortunately, creating the team features in the software proved more difficult than originally anticipated and this feature was not launched until February 2013. Teams did not have additional opportunities to earn points, as originally envisioned; however, there were some added benefits to joining teams, including team pages, team rankings, intra-city competitions between teams with natural rivalries (like city departments) and special recognition for the teams with the most points as of April 22, 2013, Earth Day.

6.3.1.5. Strategies and Activities Employed

The Challenge employed a number of strategies common to community-based social marketing (McKenzie-Mohr 2012) and behavior-based energy reduction programs (Abrahamse et al. 2005), including:

- Feedback – letting participants know how well they are doing. See (Delmas, Fischlein, and Asensio 2013) for a recent review of feedback studies. Participants received comparative feedback, showing their rank in the program as an individual and as a team. They also received points based on their usage compared to similar households. Participants could also receive personalized feedback, with recommendations to reduce their carbon footprints by using the CoolCalifornia.org carbon footprint calculator and receive Kudo Points for uploading a screenshot of their results.

- Norms –information on how others like them behave (descriptive norms) and what behaviors are expected by peers (subjective norms) (Goldstein, Martin, and Cialdini 2008). Participants regularly received communication from local program managers encouraging them to join with others in their community (a descriptive norm) and why they should participate (a subjective norm). Program newsletters also frequently highlighted California-specific descriptive norms, e.g., statistics on the percentage of Californians who recycle, compost and support energy efficiency, and how many points were earned by participants in their community.

- Social Diffusion. Social diffusion happens when individuals share their experiences through social connections (McKenzie-Mohr 2012). The CoolCalifornia Challenge tapped directly into established social networks in communities and indirectly through word of mouth, the media, email and other communications channels.

- Local leadership and capacity building. The success of the program depended largely on the ability of cities to organize a network of community leaders empowered to carry out the program. Local messengers understood local values and attitudes and were in a much better position to recruit, organize and motivate people they know than the organizers operating at the city level (Gershon 2009).

- Commitments and Goal Setting –Participants were encouraged to sign up and commit to regularly tracking energy and vehicle usage. Several goals were incorporated into the program, including becoming a "Cool California City" by entering the finalists round and becoming the "Coolest California City" for winning the competition. Participants were not given individualized goals for energy reduction, although this has also been shown to be an effective strategy (Abrahamse et al. 2005), but they were given a total collective goal of reducing 500,000 pounds of CO_2.

- Incentives. The CoolCalifornia Challenge provided recognition for participants' collective efforts as a city through their ranking in the program, and through participation in teams. Cities also had the option of using the software to select and contact raffle prizewinners, with each point counting as a raffle ticket. Raffle prizes included energy efficient products and gift cards to local stores or restaurants. One city, Chula Vista, also used seed funding for LED holiday lights and distributed them to Challenge participants in exchange for conventional holiday lights.

- Persuasive messaging. There are many strategies of effective communication (Goldstein, Martin, and Cialdini 2008). The CoolCalifornia Challenge team provided workshops, resources and one-on-one support to city program managers and community leaders on persuasive messaging, including the use of vivid imagery, stories, peer-to-peer learning, population segmentation, normative messaging and other techniques.

In addition to implementing these strategies in the software and email communications, U.C. Berkeley researchers provided workshops on community-based social marketing to finalist cities (Davis, Sacramento, Chula Vista and Tracy) and worked with these cities to develop appropriate implementation strategies during the Finalists Round. During these workshops finalist cities learned basic CBSM concepts, including 1) identifying the most promising behavior to target, 2) analysis of barriers and benefits of taking those actions, 3) developing intervention strategies, 4) piloting, and 5) scaling up interventions. Each city was encouraged to develop its own unique interventions, targeting specific actions for different populations within each city. While cities were not able to fully implement all CBSM steps, they did develop their own unique interventions. For example, the city of Sacramento developed the "Cut Your Cubes" campaign including a downtown sustainable practices scavenger hunt exclusively for Challenge participants, the city of Chula Vista conducted a holiday lighting exchange and the city of Davis began a 3-year household carbon footprint reduction campaign based on CBSM principles.

6.2.2. Research Surveys

All participants were asked to voluntarily complete a research survey during and after the competition. The survey contained four sections: demographic information, attitudes, lifestyle and EcoTeams. A full list of questions is available as Appendix A.2 in this report. As a small reward and incentive, participants earned 100 points for completing the survey. Three hundred thirty-four participants successfully completed the online survey. Six months following the end of the program participants were asked to log into the Challenge software and take a second survey that included additional questions evaluating their experience in the program (A.3). Sixty-three participants completed the second survey.

6.3.3. Experimental Design

The vast majority of behavior change programs are opt-in and therefore do not have the benefit of a true control group since those who opt-in may be different in fundamental ways than those who have not opted in. In these cases, the best option is to delay the treatment to a randomly selected portion of participants for use as a control group. In the absence of a waitlist or delayed control, a Variability in Adoption (VIA) design is considered the next best option for quasi-experiments (Opinion Dynamics/Navigant 2012; DNV-GL 2014). In VIA models, participants who opt-in to a program later are compared to participants who opt-in earlier. For example, the energy use of the control group prior to joining the program may be compared to energy use of program participants during the same time period. The two groups should be carefully assessed for similarities since the control group serves as a presumed counterfactual of the treatment group had they not joined the program.

We used a VIA model to evaluate electricity and natural gas usage. Participants were able to earn points for reporting energy usage dating back to the beginning of the program, even if they had joined late in the program. This aided in the data collection for the project as well as allowed participants to enter multiple bills at one time. Figure 26 shows the monthly number of electricity and natural gas reports that were available as a treatment group and as a control group using this method. Since participants were able to join at any point during the 13-month program, the number of households in the treatment group and control group changed on a rolling basis. The treatment group submitting reports in any given month typically ranged between 150 and 250 households. The size of the control group ranged between 55 and 275 participants prior to October 2012, but dropped to under 30 households thereafter, making comparison between the two groups at the end of the program far less accurate.

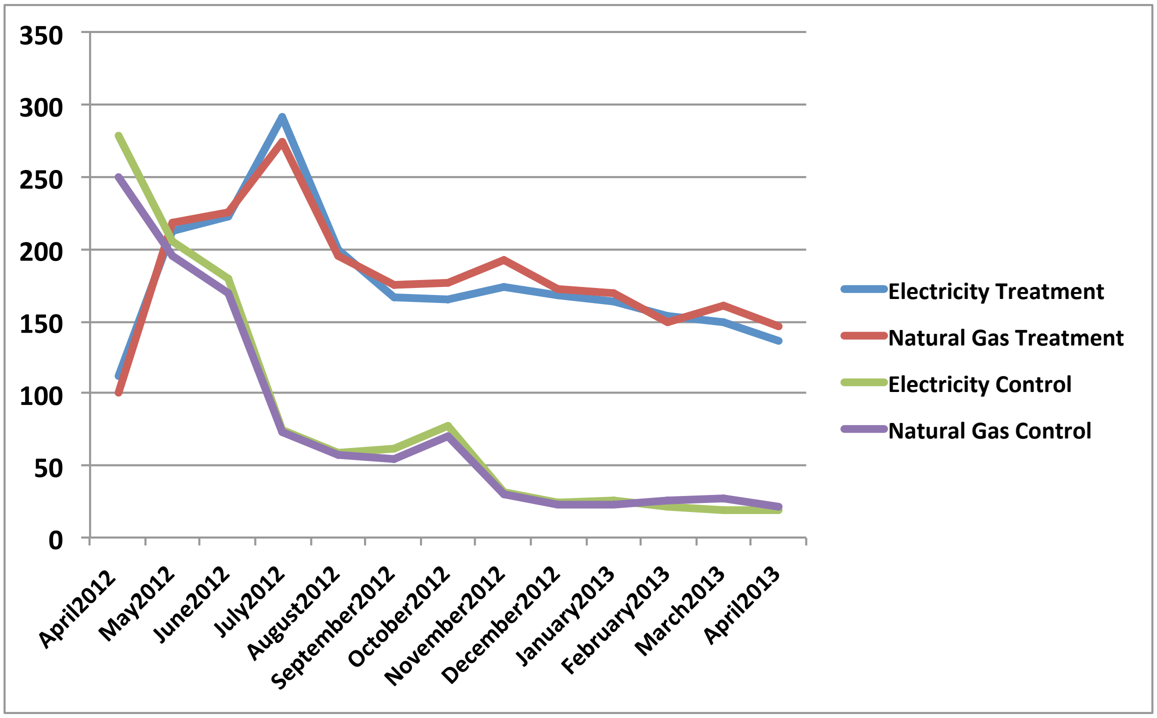


Figure 26. Size of Treatment and Control Groups

Assessment of Similarities Between Control and Treatment Groups

In order to evaluate similarities and differences between the treatment and control groups we combined survey data, which included questions on demographics and attitudes, with self-reported monthly energy data for the two groups. Of the 650 households completing at least two monthly energy data reports, 225 also filled out the research survey, providing reasonable confidence (+/- 5% margin of error at 95% confidence) that the household survey results represent the larger group of households providing energy data. However, it is important to keep in mind that the size of the control group is very small (under 30) after October 2012 and number of households who also completed the research survey for those months is smaller still. The discussion below therefore only refers to data from March 2012 through October 2012.

As shown in Figure 27, household size, age, gender and income were very similar between the treatment and control groups throughout the reporting period. Of all of these characteristics, differences in average household size would be particularly problematic; fortunately, there is a very high degree of correlation between the two groups.

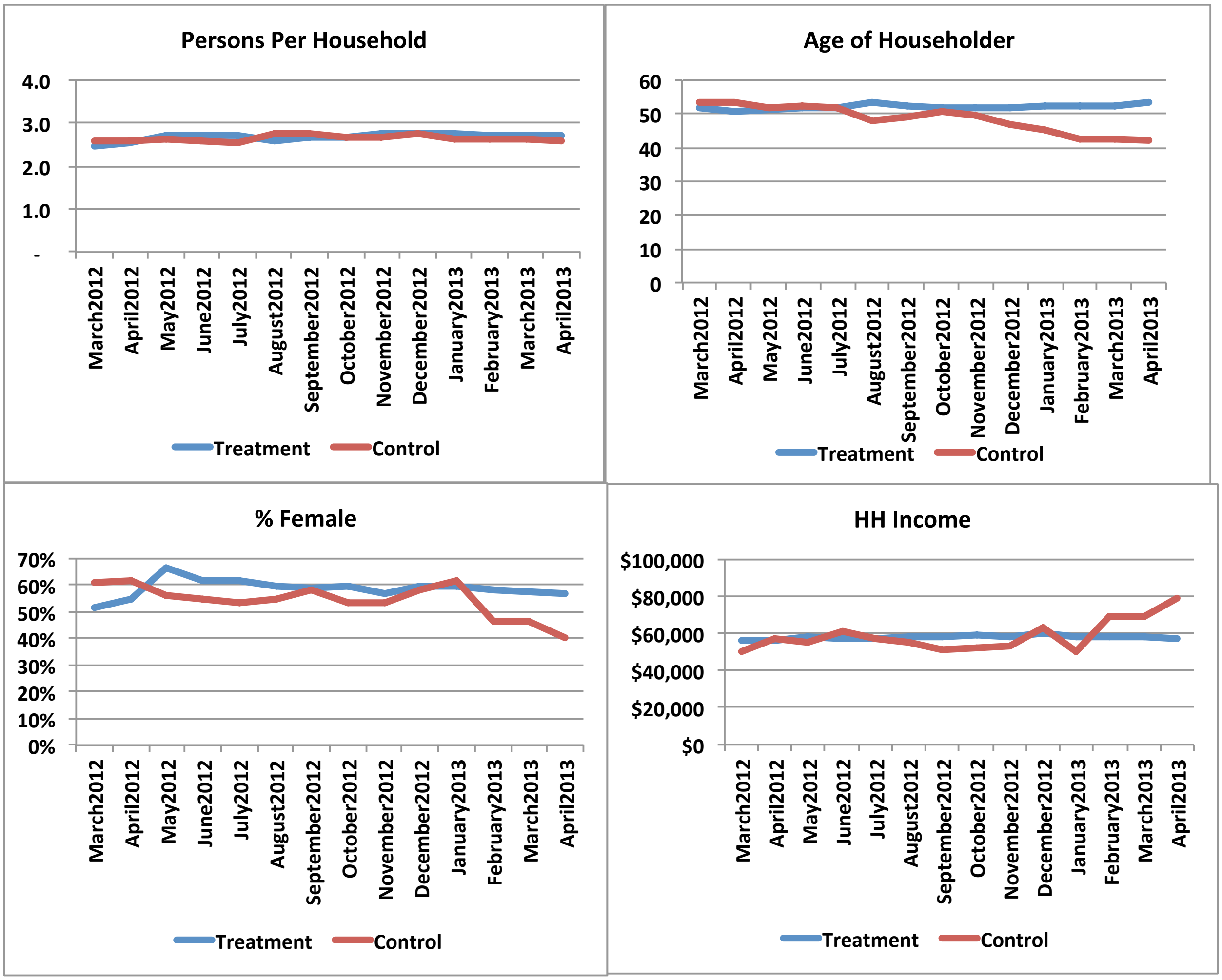


Figure 27. Household Size, Age, Sex and Income of Treatment and Control Groups

Political party affiliation and level of education varied somewhat between the control and treatment groups (Figure 28). These characteristics have been shown to be strongly correlated with views on climate change (Maibach, Roser-Renouf, and Leiserowitz 2009), with more conservative and less educated households being less likely to believe in or be concerned about anthropogenic climate change. The treatment group is somewhat more conservative and less educated and may therefore be less motivated to reduce greenhouse gas emissions than households the treatment group, potentially weakening the experimental design. An alternative explanation, however, is that fraction of households living in more or less educated and politically liberal cities, in either the treatment or control group, changes over time. Thus, controlling for city could reduce the differences.

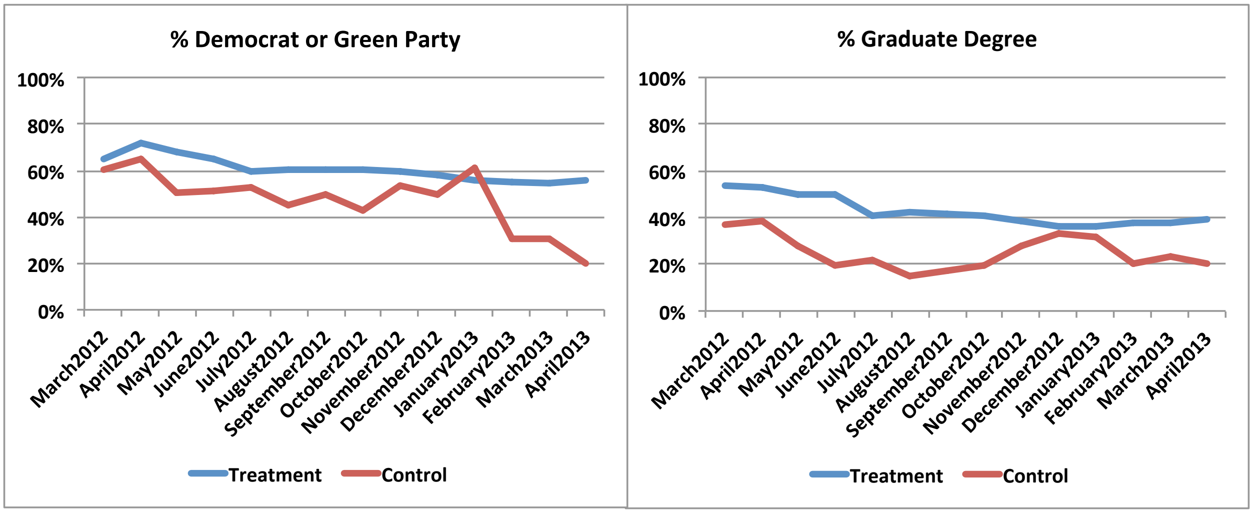


Figure 28. Political Party Affiliation and Graduate Degree Attainment of Treatment and Control Groups

As shown in Figure 29, the fraction of Davis households in the control and treatment groups varies to a similar degree as the variables shown in Figure 26. Davis participants are also much more likely to have a graduate degree than other cities (53% compared to 25%, on average) and are also more politically liberal. This lends evidence that the differences between the control and treatment group may be at least partially due to the composition of cities in each group over time.

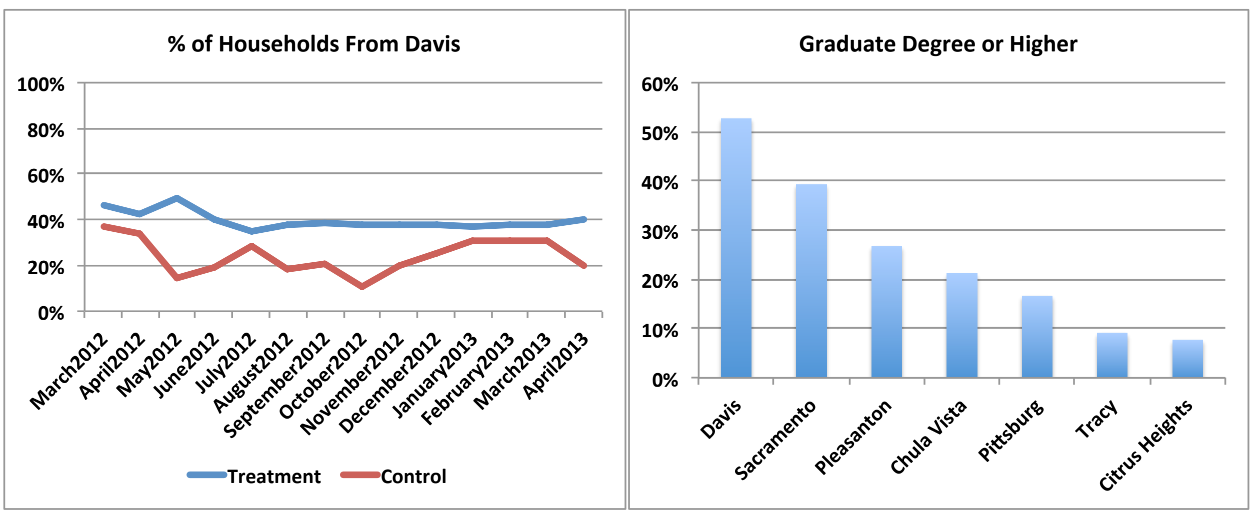


Figure 29. Graduate Degree by City and Fraction of Households from Davis

Figure 30 shows the number of households reporting electricity in each city for every month of the competition for both the treatment and control groups. During the first few months the number of reporting households in the treatment group grew to saturation level in about August, after which monthly reporting remained fairly constant at about 500 households per month. The fraction of households from each city in the treatment group stays fairly constant throughout the program period, but the fraction of households from each city varies considerably for the control group. This is shown best in Figure 31, which shows the same data as in Figure 30 but by percentage. Cities not only have different compositions of political affiliation and educational degree attainment, but differences in weather, energy policies, culture and other characteristics, so controlling for city is critical to the experimental design.

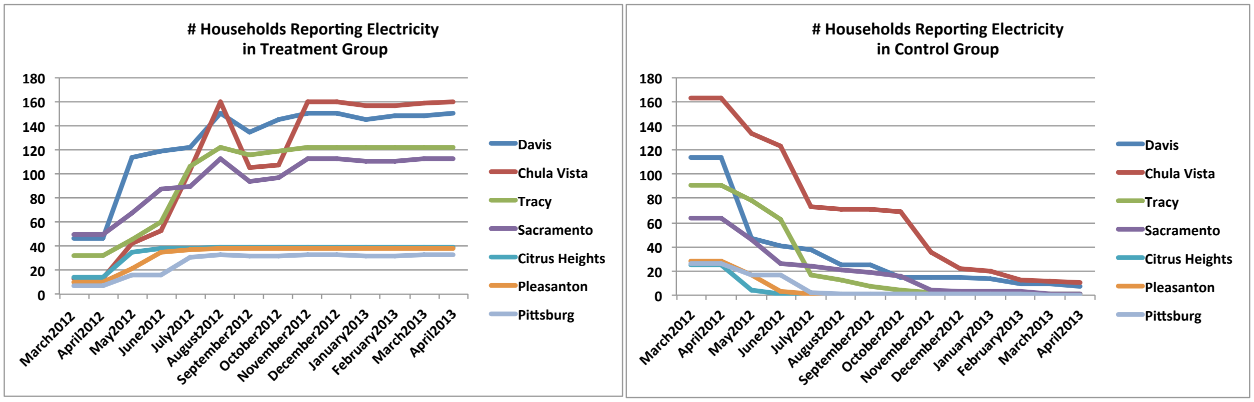


Figure 30. Number of Households Reporting Electricity in Treatment Group by City

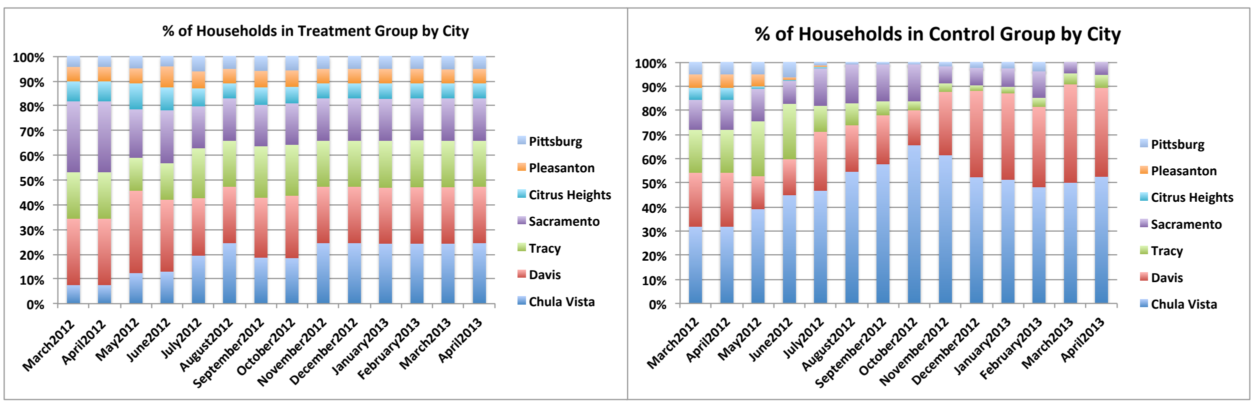


Figure 31. Fraction of Households in Treatment and Control Groups by City

Due to the very small sample size of households completing both the research survey and energy reports in each city it was not possible to examine the composition of control and treatment groups for each city; however, as expected, simply removing Davis households from the analysis does considerably reduce differences between the two groups. See Figure 32, which compares educational degree attainment with and without Davis households. Households in the treatment group for the remaining cities were somewhat more likely to have higher education than the control group; however, controlling for all cities may further minimize these differences, as well as differences in political party affiliation.

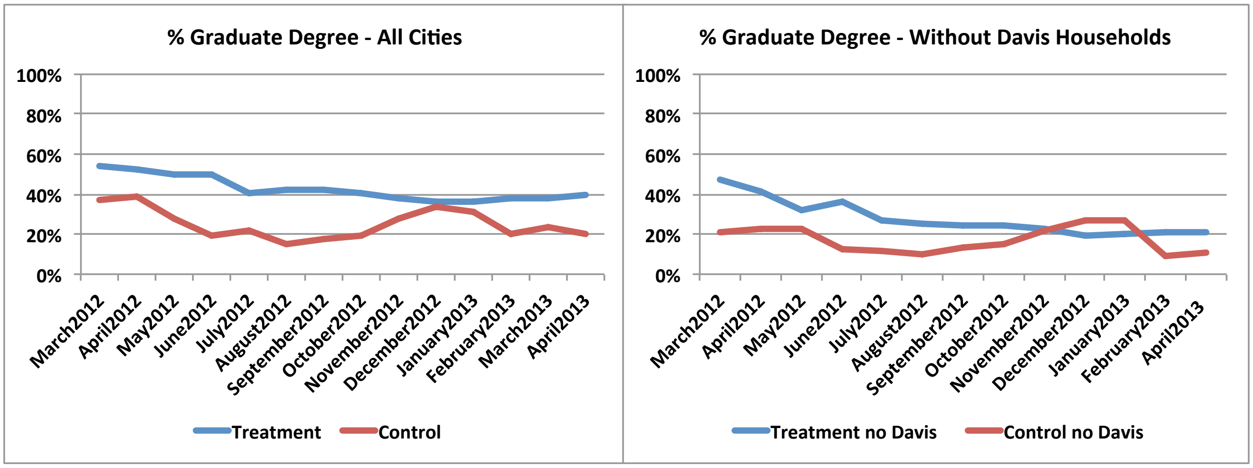


Figure 32. Graduate Degree Attainment with and without Davis

To account for differences between cities, we adjust each monthly household energy report as follows:

$EU_{kt} = REU_{kt} / (AEU_{ct} / AEU_t)$

Where,

EU_{kt} is the energy use (electricity or natural gas) for household k in month t
REU_{kt} is the reported energy use for household k in month t
AEU_{ct} is the average energy use of all participants reporting in city c in month t
AEU_t is the average energy use of all program participants in month t

This approach normalizes average monthly energy use in each city to the average monthly energy use in all cities, for both the control and treatment groups, thus accounting for differences in weather, energy policies, housing stock, household characteristics and other factors that affect energy usage between cities.

Given the similarities in most demographic variables, and the additional control for location, we assume the control group acts as a counterfactual for the treatment group had they not joined the program. Nonetheless, it does make sense that the most motivated participants would join earlier, and less motivated participants would join later. This is a fundamental limitation with the VIA model that is not entirely possible to control for in this study. Given the small sample size of households completing survey responses and reporting energy in each city, multivariate regression techniques (see Opinion Dynamics, 2009; and DNV-GL 2014) were not possible to further align the control and treatment groups beyond the normalization by city.

We have limited our impact evaluation to electricity and natural gas. While several hundred participants also regularly recorded odometer readings of their vehicles, the majority of households only tracked one vehicle, particularly during the first months of the program. Since most households have more than one vehicle, we assumed this was a reporting error (and also a problem with the feedback initially provided by the software to reduce this error) so we were not able to accurately evaluate reductions in household motor vehicle usage. It should be noted though that greenhouse gas emissions from motor vehicles are about three times larger than household energy GHG emissions in California (Jones and Kammen 2011) so total GHG reductions due to the program are likely considerably higher than those reported here.

6.2.4. Supplementary Interviews

Several months after the end of the program, city program managers were asked to be interviewed about their city's experience participating in the program. The interview included questions on their city's motivations for joining the program, the resources they had at their disposal to run the program, their evaluation of each of the main program activities, their opinion on the outcome and results, and their recommendation for future programs (Appendix A.4). Six city program managers completed the interviews.

6.3. Results

6.3.1. Participation

Figure 33 shows level of participation throughout the 13-month program as measured by number of new participants and number of monthly electricity reports. The vast majority of new enrollments (67%) joined during the Qualifying round, April 1 through July 31. Participation in the program, as measured here by the number of times households reported electricity, first peaked in May, when the first finalist city, Davis, was announced. Sacramento was then able to secure the second spot at the end of June without considerable competition and with somewhat lower overall level of participation. Chula Vista and Tracy engaged in a very intense competition for the last spot at the end of July. As was noted earlier, these two cities were almost exactly tied at the end of July and were both declared finalists in the program. There was another boost in enrollment in the first few months of the Finalists Round (fall 2012), but starting in January 2013 new sign ups were minimal. Participation was lowest in winter months when there were no program deadlines. The largest peak in participation was the last month of the program, when 33% of electricity reports were recorded. Based on this evidence it is clear that the timing of the program deadlines played a critical role in participation levels throughout the program.

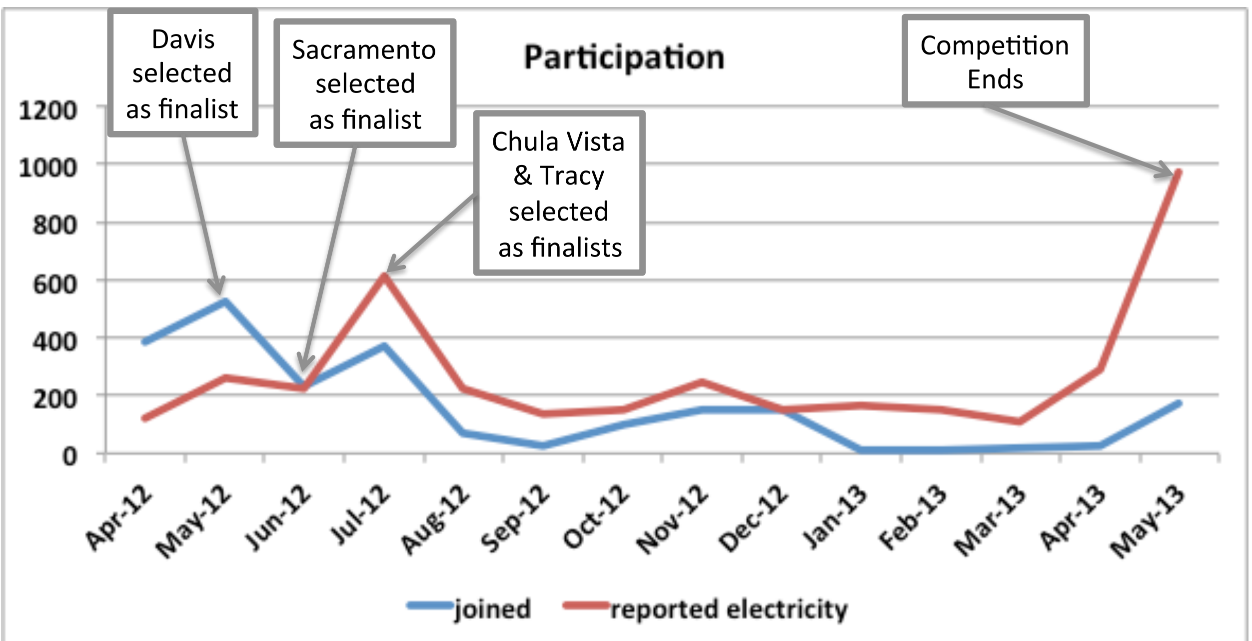


Figure 33. Participation Levels

6.3.2. Energy and GHG Reductions

Electricity

From April through October 2012, when the control group contained a sufficient number of subjects for a reasonable control, Challenge participants used 14% less electricity than the control group (Figure 34). During the entire 13-month program the treatment group used 19% less electricity than the control group; however, due to the limited sample size of the control group after October we consider the lower estimate of 14% to be a more realistic estimate of total annual program savings. Savings were greatest during peak periods in summer and winter. Curiously, electricity demand was slightly higher in December and January than in August, the hottest summer month, for both the treatment and control groups. It is unclear why this occurred, but it may be due to additional electric space and water heating during the coldest months and more days spent at home during holidays. Electricity consumption was very similar between the two groups in March 2012, one month prior to the start of the program, and through the first three months when households were signing up for the program.

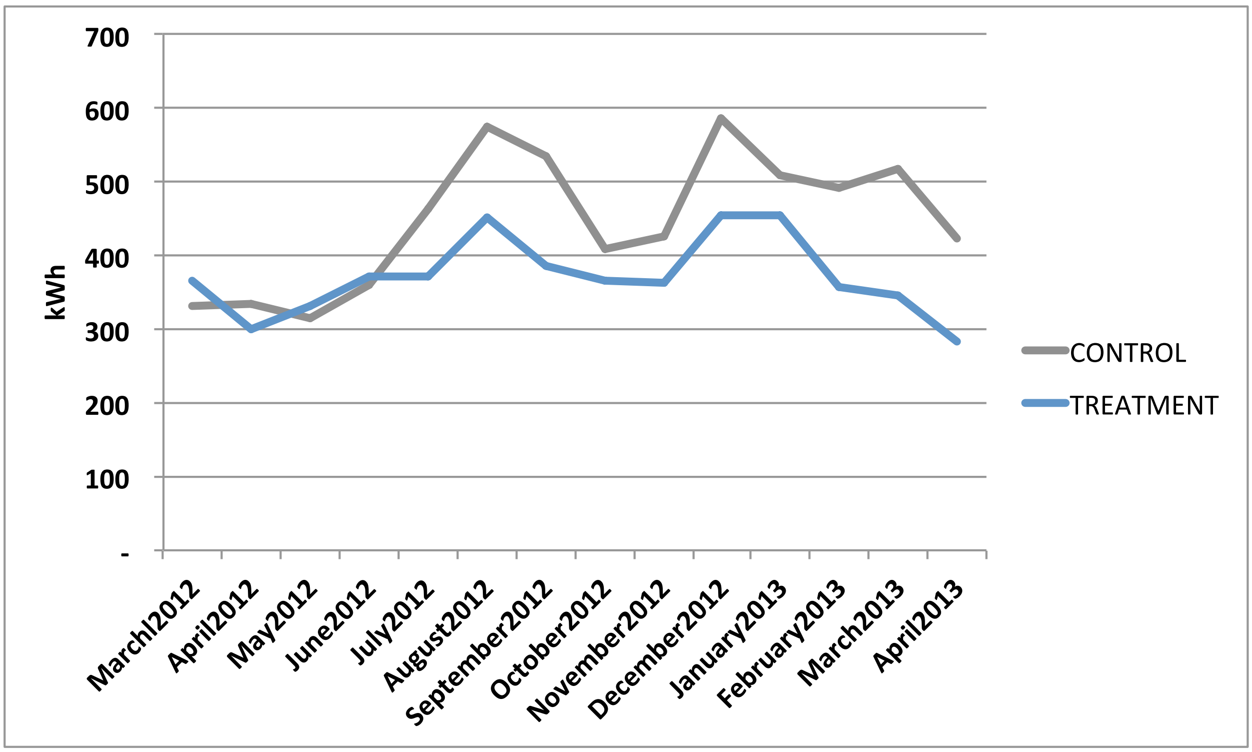


Figure 34. Electricity Consumption of Treatment Group vs. Control Group

Electricity consumption varied considerably by city and also, of course, between households within cities (see Figure 35 and Appendix A.1 for summary statistics). Since the program was opt-in, most participants did not enter data for the first few months of the program so the sample size of each city is quite small until about July or August when each city consistently had over 100 entries per month (Figure 33). It is therefore not possible to evaluate the overall trend for each city. Even if this were possible it is important to note that increasing consumption would not be an indication of lack of a program effect since consumption increased considerably more for the control group than for program participants and the data presented below are not normalized by weather.

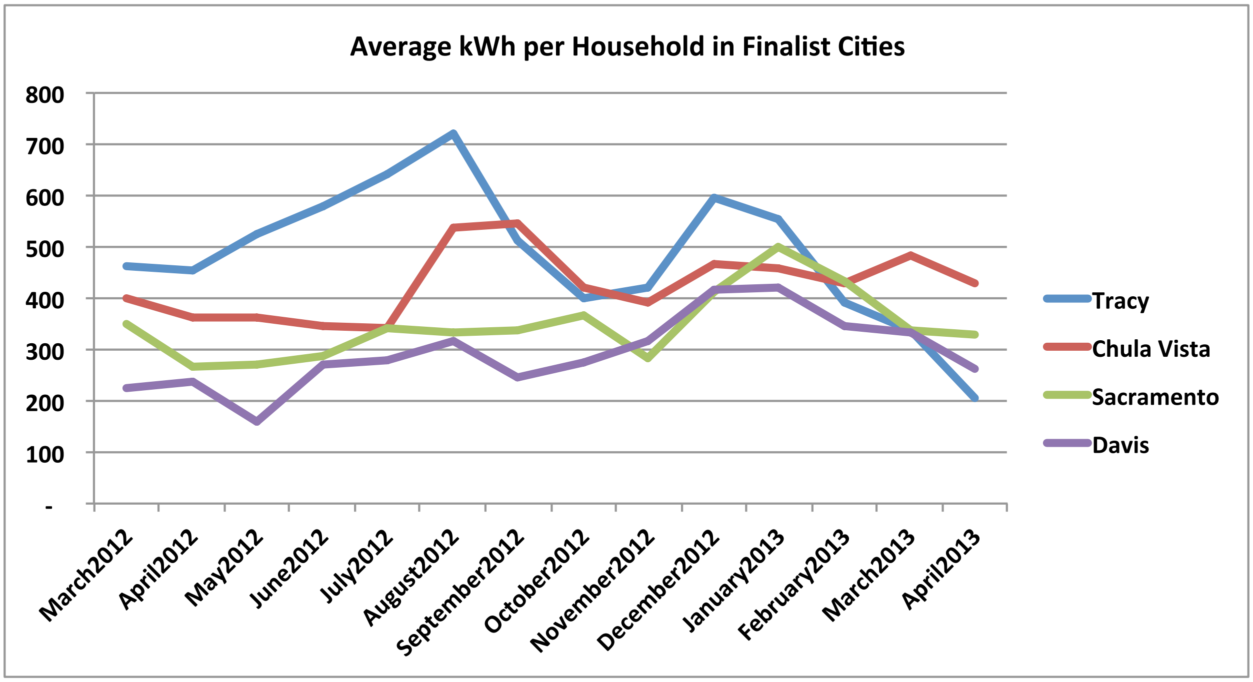


Figure 35. Average Monthly Electricity Consumption by City

Natural Gas

In contrast to electricity, participants demonstrated essentially no savings in natural gas consumption (Figure 36). Between April and October, when the size of the control group was between 55 and 275 households, both the treatment and control groups used exactly 97.8 therms and monthly usage was quite similar with no clear pattern. After October the size of the treatment group falls to below 30 households, so we are not able to evaluate usage with any statistical confidence. For comparison purposes we have included the California benchmark value, as computed by the software (Jones and Kammen, 2014) and adjusted for average California consumption of 6,992 kWh/yr (U.S. Energy Information Administration 2005). Natural gas consumption in summer months was about 50% below that of average California households with similar location, size and age of householder, but 20% higher during the winter heating period. The benchmark is a modeled result and not a statewide average, but it does help confirm that natural gas was likely not reduced in winter months (see the Discussion and Conclusion sections for potential reasons why there were no savings of natural gas). While there are no measurable savings in natural gas, the close alignment between the control group and the treatment group through October 2012 suggests that the experimental design is sound and calculated savings in electricity are realistic.

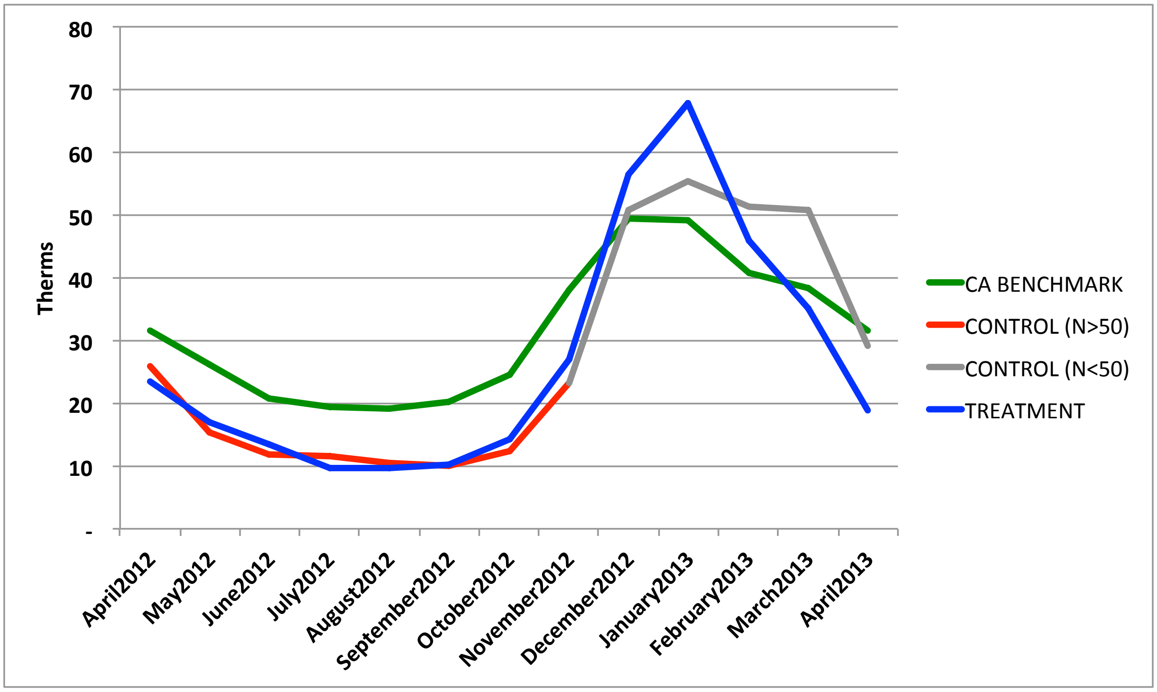


Figure 36. Natural gas consumption of treatment and control group, and California benchmark

Total Energy and CO_2 Savings

The analysis above considers only participating households that entered electricity or natural gas reports in any given month. Multiplying monthly electricity savings in each month by the number of reporting households, summed over the 13 months of the program translates to 183 MWh of electricity savings, equivalent to the average annual electricity consumption of 23 California homes, and about 50 metric tons of CO_2. This does not include any savings for active households when they did not report electricity or any potential savings from households not reporting electricity. It also does not include any potential savings from motor vehicles, which were not calculated for this study. An alternative method of determining CO_2 savings in real time during the program was to divide Bonus Points by 3 to account for reductions below participants' performance in previous months. Using this methodology we calculated a program-wide savings of about 495,000 lbs (227 metric tons) of CO_2, approximately reaching the stated goal of 500,000 announced several months prior to the end of the program.

6.3.3. Survey Results

In the figures below we provide descriptive results from the survey responses and compare points earned by different groups of subjects.

6.3.3.1. Demographic Characteristics

Nearly 50% more women completed the research survey than men (Figure 37). Online Challenge accounts were linked to one email address per household. We therefore assume that the person who completed the research survey was also likely to be responsible for administering the program within the household. Households in which men completed the research survey earned an average of 33% more points than women who completed the survey; however, in total women earned 40% more points than men because women represented more of the participating households. Only 14% of participants who completed the survey were between the ages of 18 and 34. While this age group was initially an important target audience (mostly "striving believers"), young adults were more difficult to recruit into the program. Young people also scored, on average, less than half the points of participants in other age groups. This may partly be explained by the large fraction of young people who are likely renters, but it also may reflect lower levels of interest and participation generally. All other age groups earned a similar amount of points.

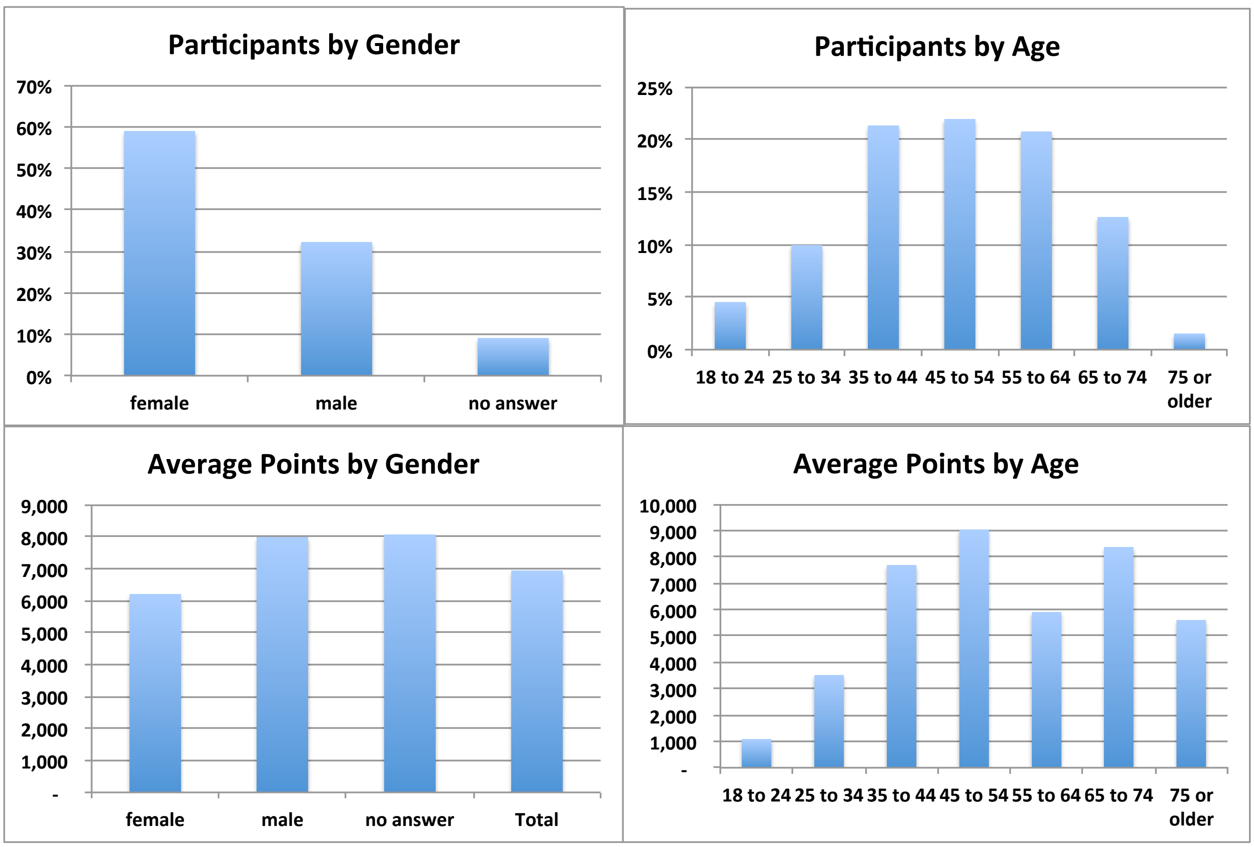


Figure 37 Points Earned by Sex and Age of Respondent

Figure 38 shows participation across income levels and education attainment. Participants were well represented across income levels and participants were only slightly more likely to earn points at higher incomes than at lower incomes. Education had a much stronger impact on points, with respondents who hold graduate degrees earning more than two times as many points as participants without a college degree.

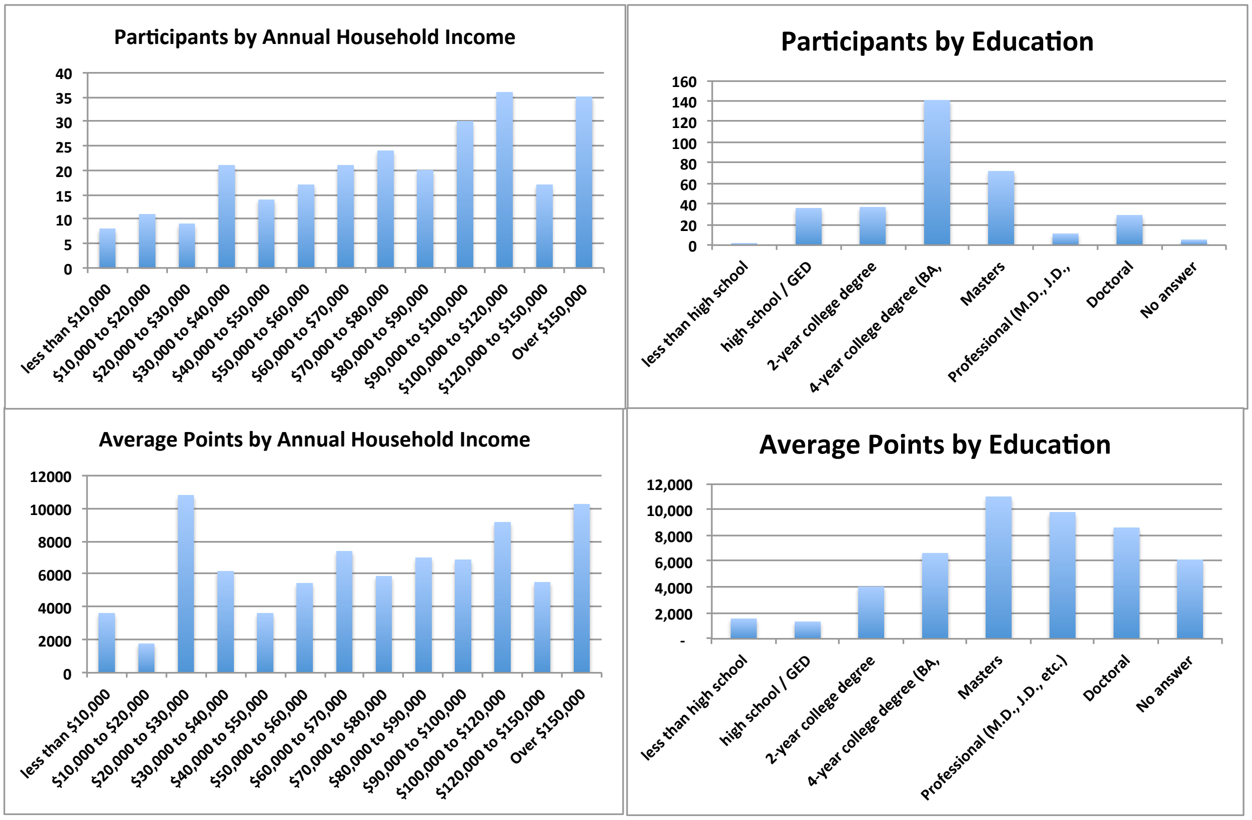


Figure 38. Participation and Average Points by Income and Education

Figure 39 shows participation levels and average points earned per household by level of conservatism and political party affiliation. As expected, most participants were politically liberal (76%) and Democrats (60%); however, 12% of those who answered this question self-identified as conservative and 14% as Republican. Somewhat surprisingly, conservatives and Republicans earned only about a third fewer points, on average per household, than liberals and Democrats.

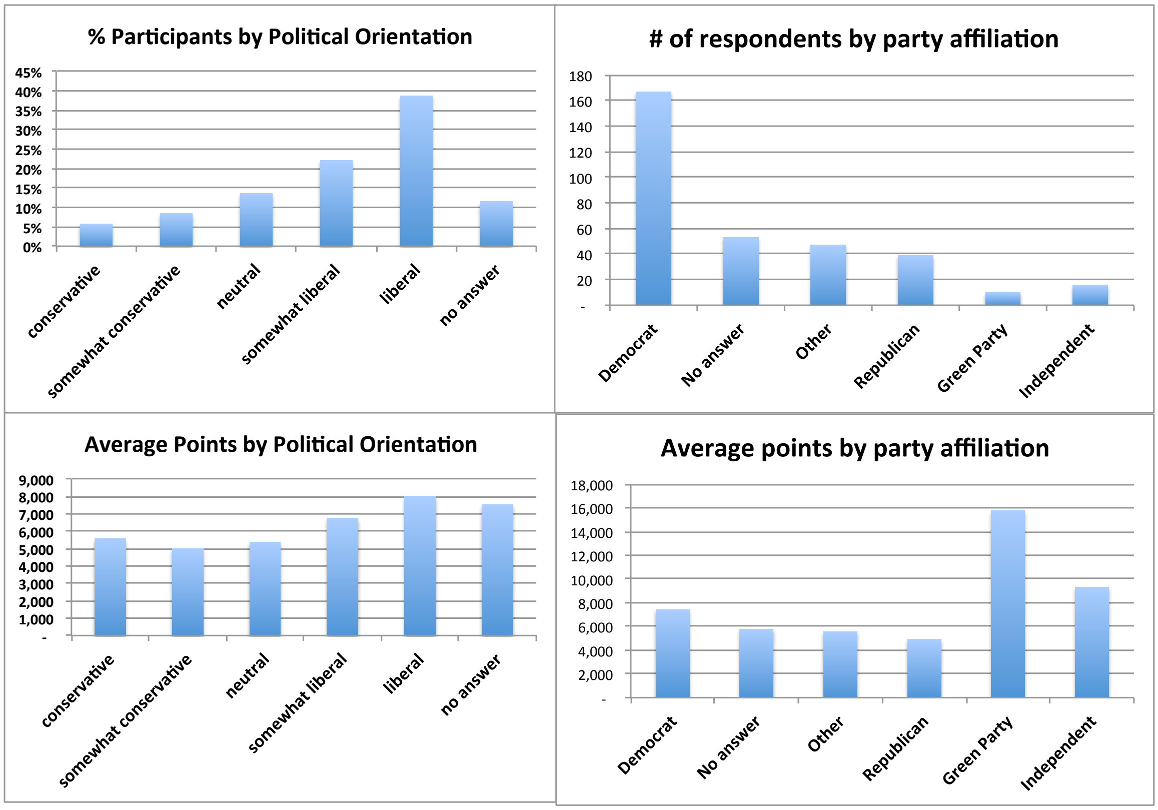


Figure 39. Participation and Average Points by Political Orientation and Political Party

A recent ARB-funded study (Delmas 2013; Chen, Delmas, and Kaiser 2014) providing energy feedback to residents of family student housing found that households with children reduced more energy than households without children. We were not able to replicate this finding in the Challenge (Figure 40); households without children earned more points than households with one or more children. However, in the previous ARB study, this finding was only robust in cases where households were receiving information about the health impacts of air pollution associated with electricity use so results are not directly comparable.

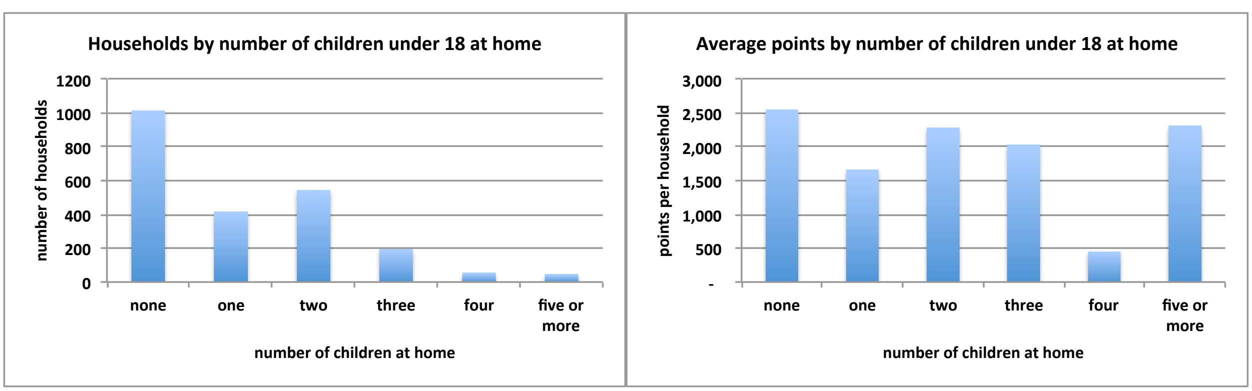


Figure 40. Number of Households and Points per Household by Number of Children at Home

6.3.3.2. Lifestyle & Behaviors

Most participants heard about the program from the city government or another participant, friend or colleague (Figure 41). This suggests that social networks and social diffusion were effective strategies to encourage program participation. While most survey respondents only checked one box, many noted that they heard about the program from multiple sources. It is possible that many respondents in fact heard about the program from multiple sources, but simply checked one box.

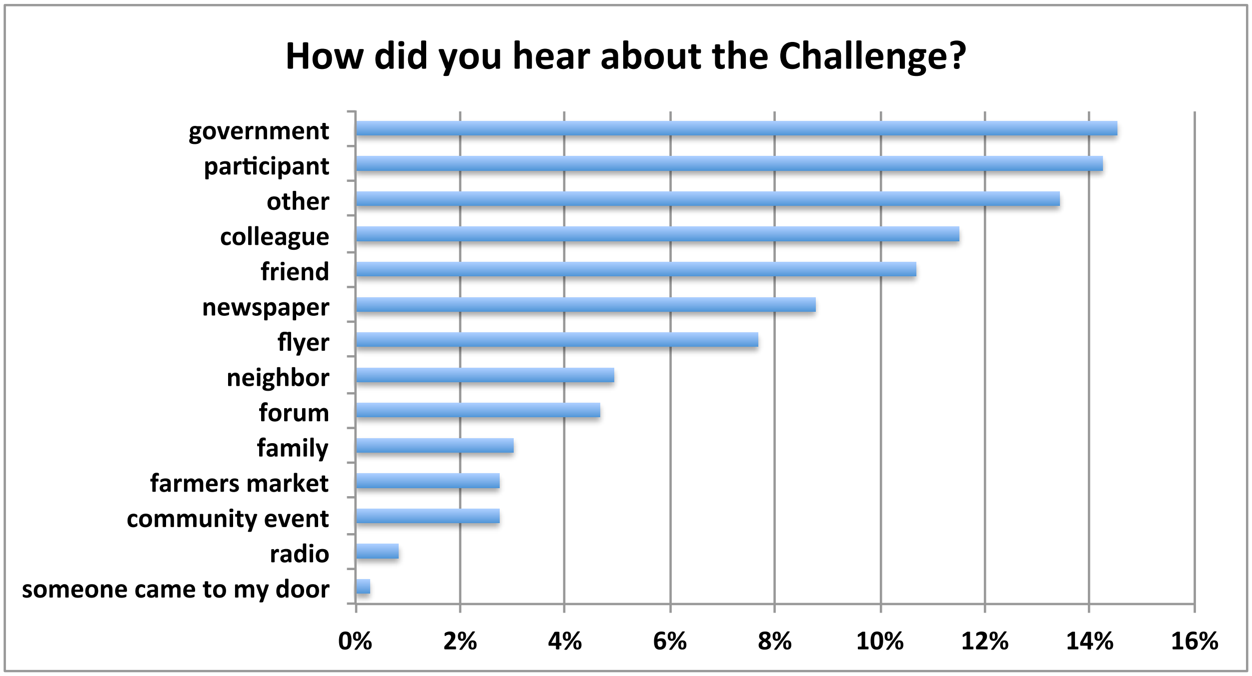


Figure 41. How Participants Heard About the Challenge

Respondents demonstrated strong pre-existing participation in low carbon lifestyles (Figure 42). Over 60% of respondents ride their bicycle at least once a week during nice weather and about 40% ride their bicycles even when the weather is not nice. About 50% of participants compost, presumably mostly in their own yards since curbside food waste collection for municipal composting is not available in participating cities. Sixty percent of participants eat a vegetarian meal at least once a week. Thus, the program seemed to attract households who have largely already taken a number of actions that the program recommends prior to joining.

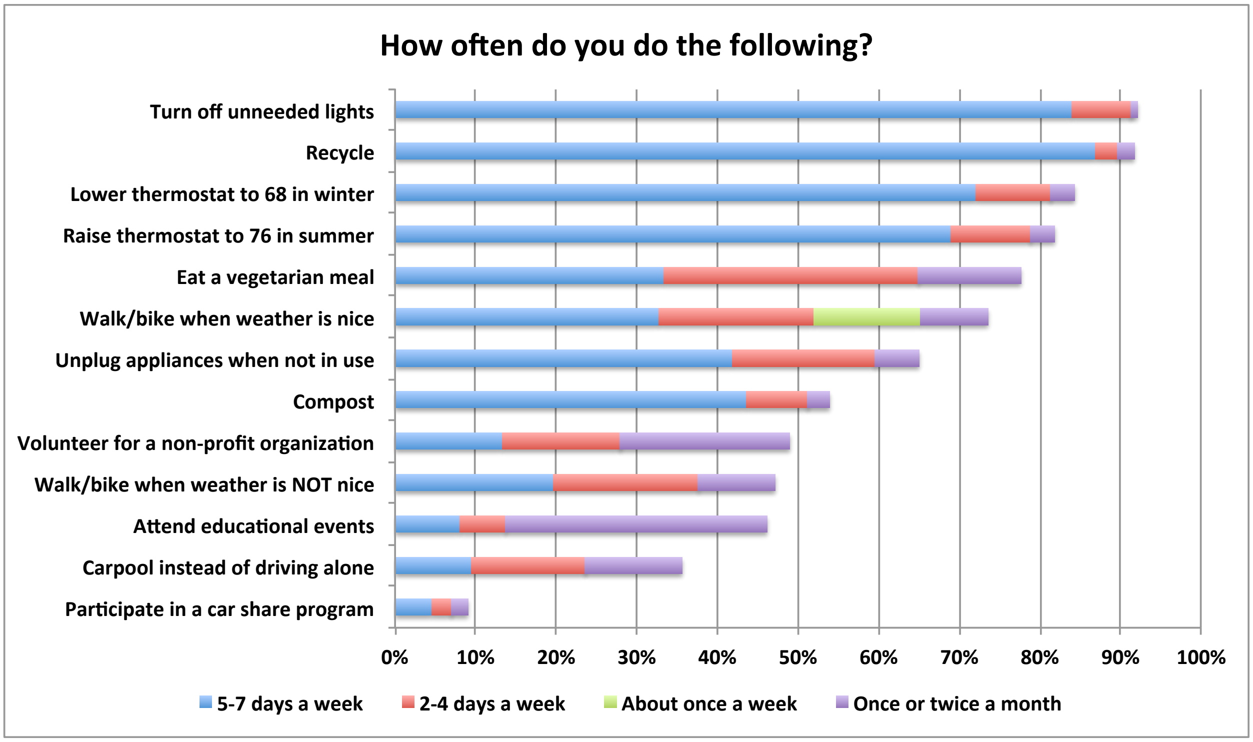


Figure 42. Low Carbon Practices of Participants

Far fewer respondents have purchased energy efficient products or appliances (Figure 43). While over 70% have purchased energy efficient light blubs, only 20% reported purchasing an energy-efficient appliance and less than 10% had insulated their attic, weather-stripped their home or installed an energy-efficient furnace, water heater or air conditioner.

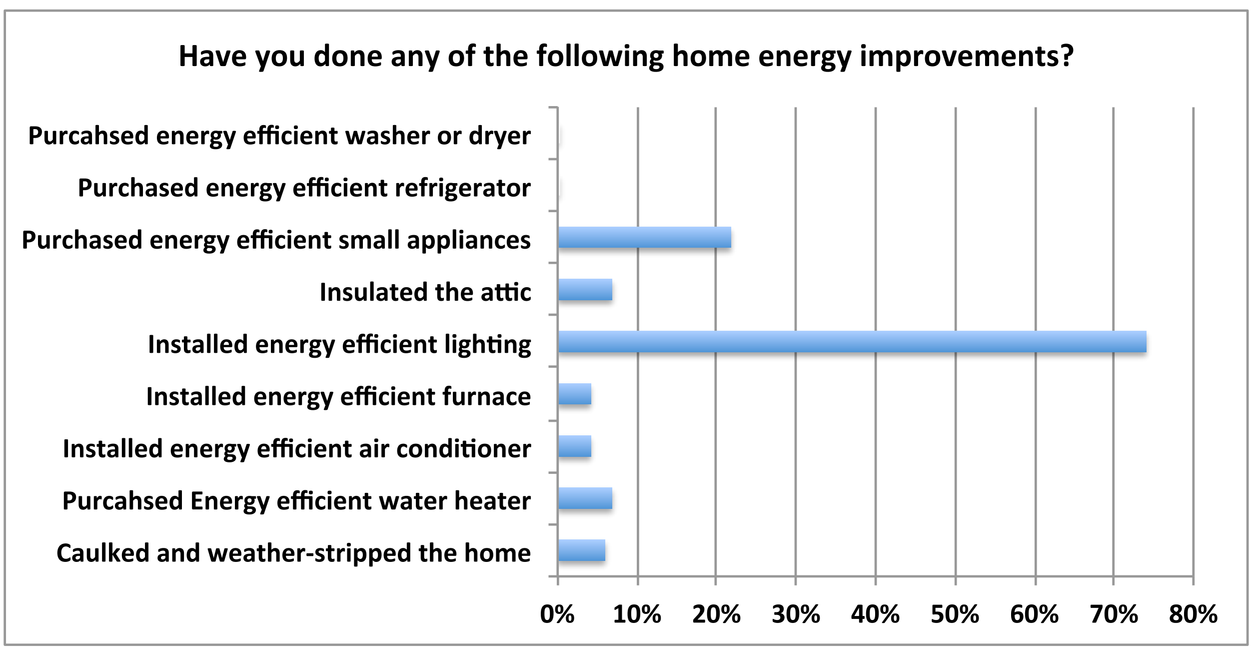


Figure 43. Energy Improvements Taken by Households

Over 30% of respondents owned a vehicle that gets over 30 miles per gallon and 15% owned either a hybrid electric, plug-in hybrid or all electric vehicle. Fifteen respondents even reported owning either an electric bicycle or a neighborhood electric vehicle. (Figure 44)

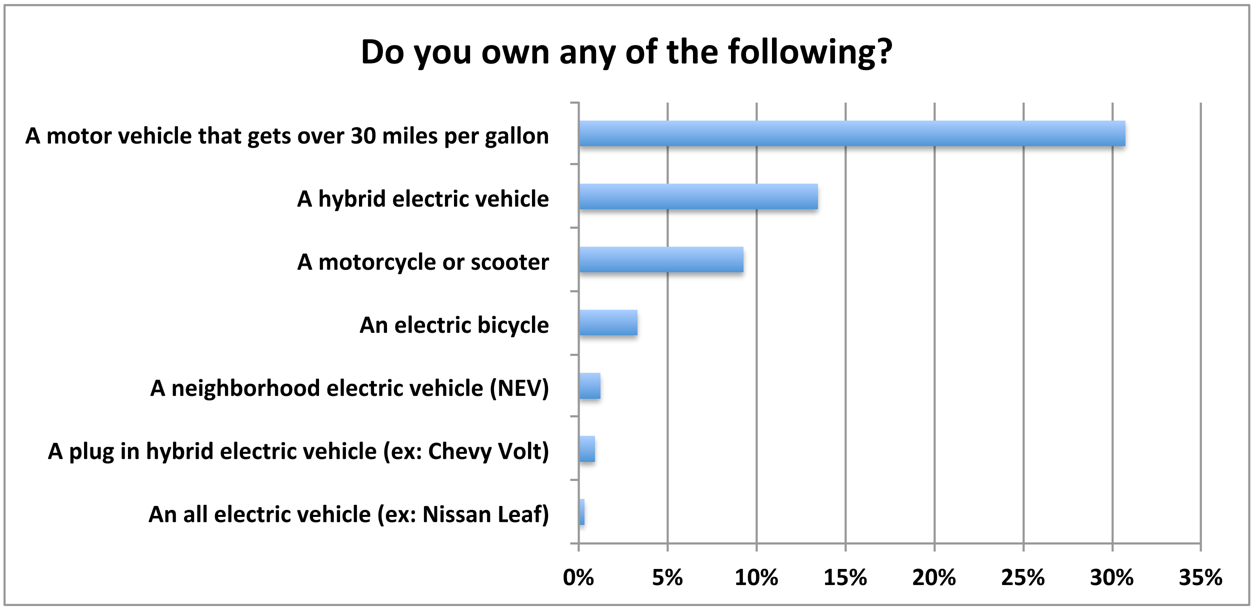


Figure 44. Ownership of Fuel Efficient and Electric Vehicles

6.3.3.3. Opinions and Attitudes

About 90% of respondents reported being either very well informed or fairly well informed about the causes of global warming and "ways in which we can reduce global warming" (Figure 45). Those who reported being very well informed earned over twice the number of points per household than those who were less informed about the causes of global warming and nearly three times as many points than those who were not well informed about personal actions to reduce global warming.

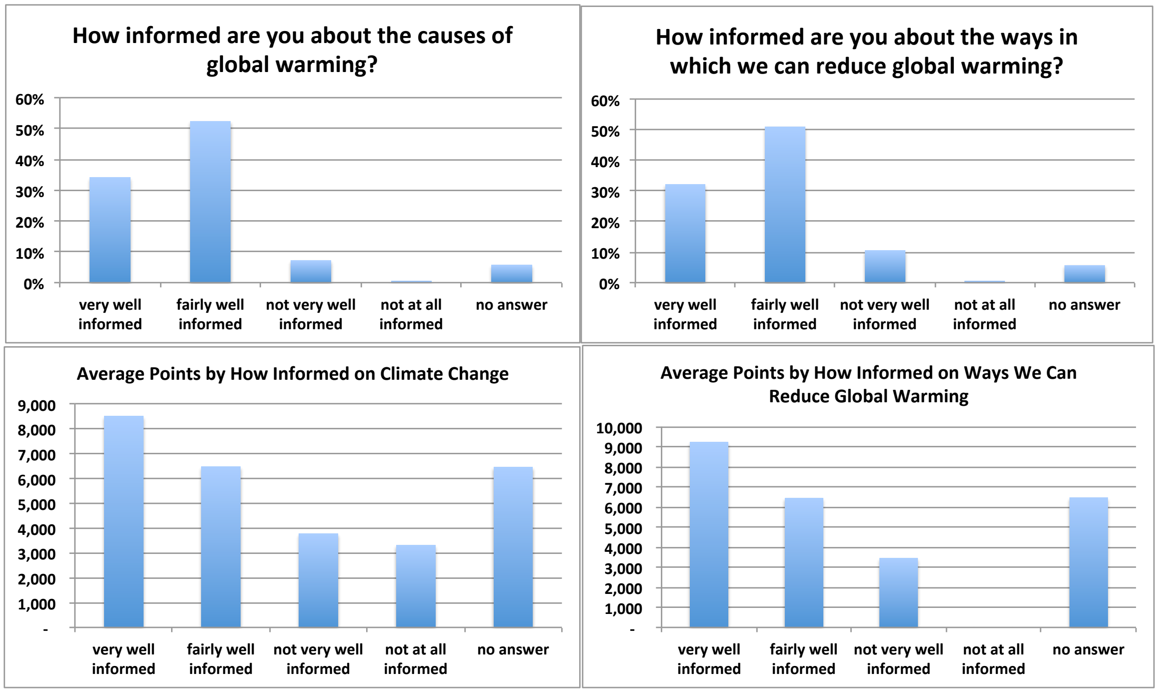


Figure 45. Participation and Points by Level of Information about Global Warming

Nearly 80% of respondents believed global warming is mostly caused by humans, while nearly 10% of respondents believed global warming was caused mostly by natural causes or that it was not happening (Figure 46). Surprisingly, those who were skeptical of human-induced global warming still earned about half as many points in the Challenge as those were convinced, reflecting a fairly high level of engagement in the program despite a clear lack of a climate change related motivation.

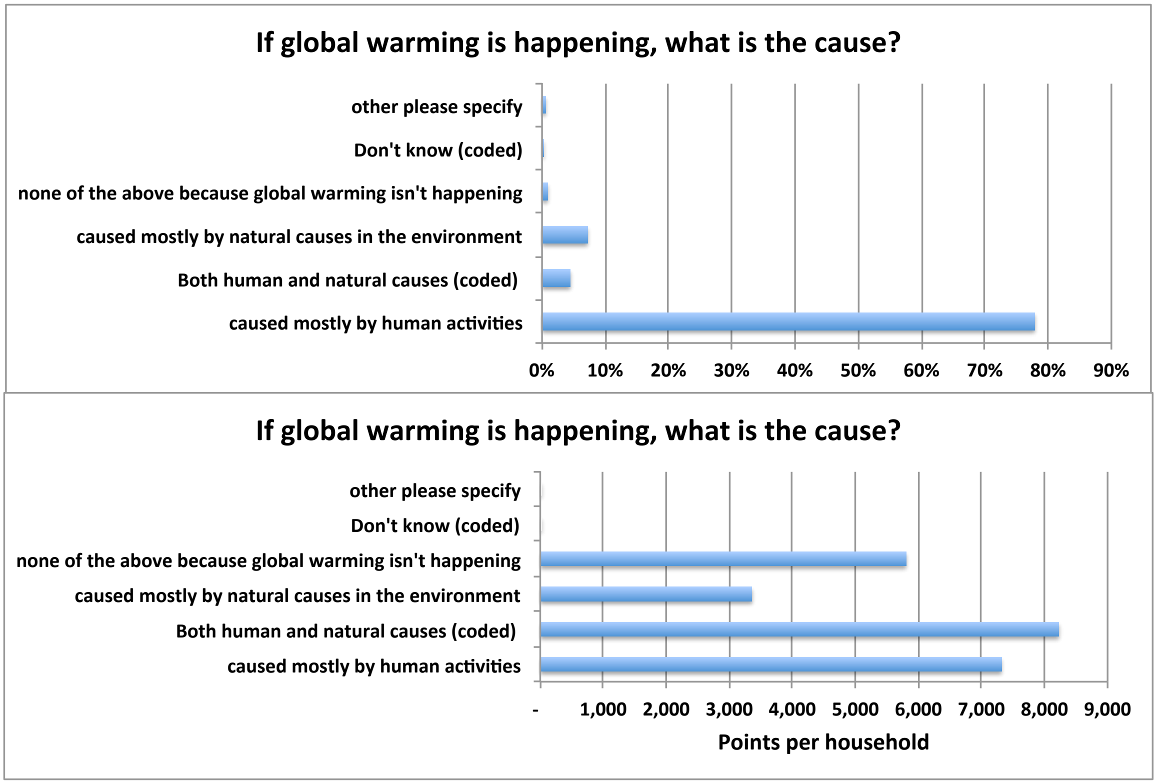


Figure 46. Belief in Human-Induced Global Warming

Most participants either agreed or strongly agreed that their actions "can make a difference to reduce global warming" (Figure 47); however, even those who did not agree or only somewhat agreed earned almost as many points per household.

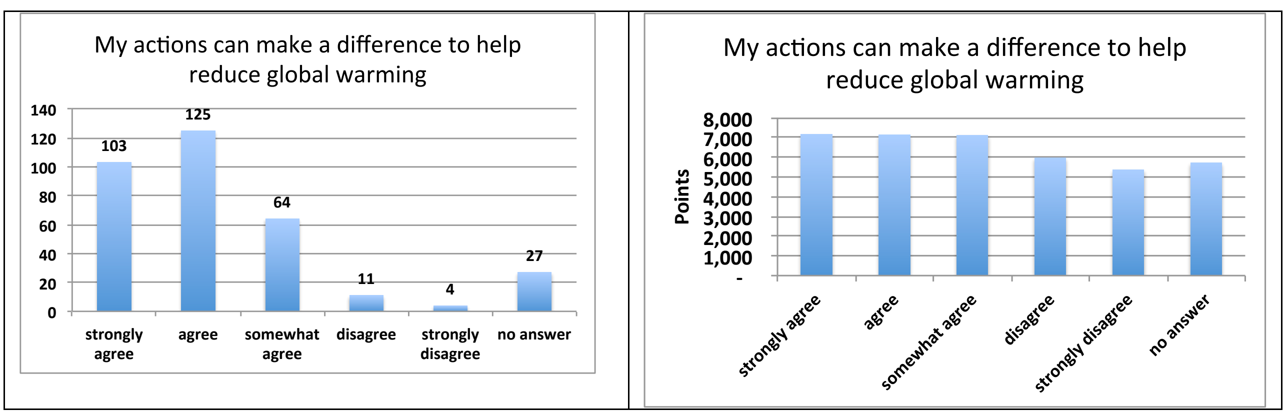


Figure 47. Belief that Their Actions Make a Difference

6.3.3.4. Primary Motivations and Values

Participants were asked to rate the importance of joining the Challenge from a list of motivations. Responses (Figure 48) reflect primarily altruistic and intrinsic motivations. Topping the list, with over 90% of respondents rating as at least somewhat important, were "improving where you live," "supporting organizations you care about" and "making an environmental statement." "Learning about new technologies" and "being part of something important" may also be considered intrinsic motivations, reflecting pleasure in understanding and participating in climate action. Extrinsic motivations of saving money and earning discounts also rated high; however, less than a third of participants ranked winning prizes as either important or very important. Living in a "Cool California city" and earning recognition for their city was either important or very important for over half of respondents.

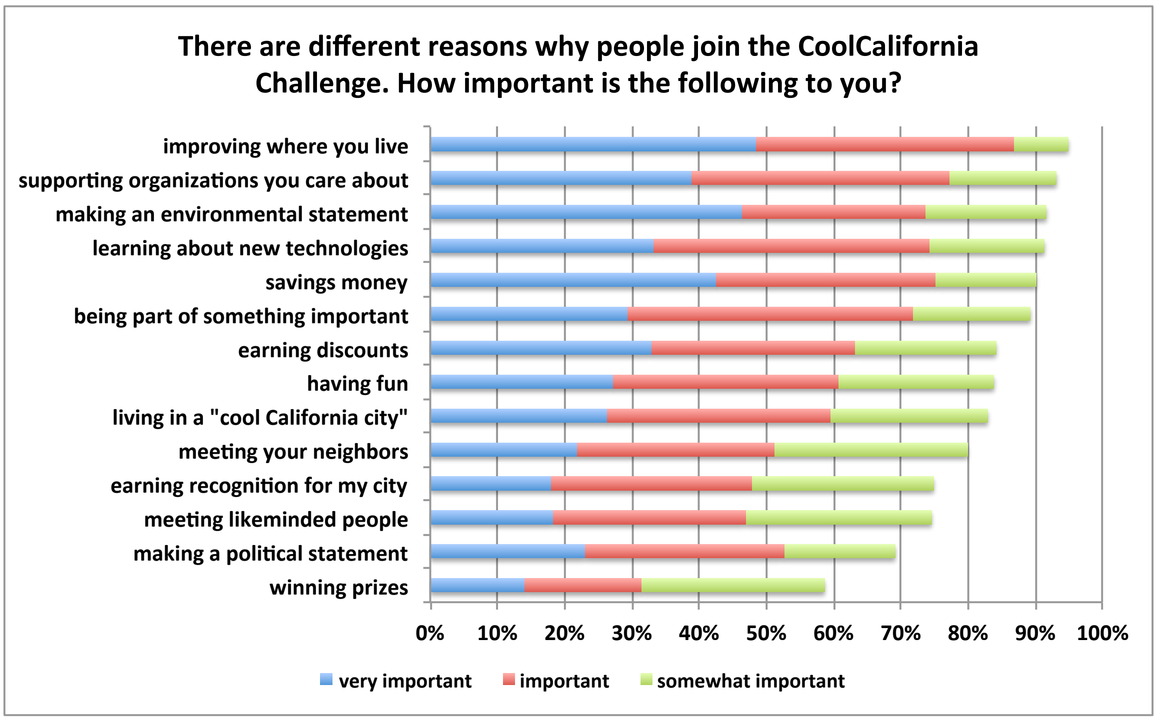


Figure 48. Primary Motivations for Joining the Challenge (all Participants)

Figure 49 compares motivations of participants based on different demographic characteristics, political party affiliation and belief in human-induced global warming. Answers were coded on a Likert scale from 0 (not important at all) to 4 (very important). There is remarkable consistency in the strength and rank of the top motivations across age, gender, income and education, although minor differences may be noticed. Young, less educated and lower income participants (who are often the same people) expressed slightly more interest in learning how to save money, receiving discounts and, somewhat more noticeably, winning prizes. "Having fun" rated slightly higher for participants under 35, although only marginally (3.1 vs 2.7). "Getting to know your neighbors" was slightly less important for men (2.3 vs. 2.7). Republicans and conservatives (combined as a single category) and "climate change skeptics" (lacking a belief in anthropogenic climate change) were also primarily motivated by helping their community and supporting organizations they care about, although saving money was the highest-ranked motivation, making an environmental statement was not a top motivation, and making a political statement was not important (and potentially off-putting) for conservatives, as well as for less educated participants. Somewhat surprisingly, participants who signed up for the program but did not earn any points reported somewhat higher motivations than those who earned over 5,000 points (on average of 2.9 vs 2.7).

	KEY
Very important	4.0
Important	3.0
Somewhat important	2.0
Not very important	1.0
Not important at all	-

The following is a list of reasons why people are interested in joining the CoolCalifornia Challenge. How important is the following to you?

Motivation	All participants	Under 35 years old	Over 35 years old	Women	Men	Under $70k household income	Over $70k household income
Improving where you live	3.4	3.7	3.4	3.5	3.3	3.4	3.5
Making an environmental statement	3.2	3.0	3.3	3.3	3.1	3.2	3.2
Supporting organizations you care about	3.2	3.3	3.2	3.3	3.0	3.2	3.2
Learning how to save money	3.2	3.4	3.1	3.3	3.1	3.3	3.1
Learning about new technologies	3.1	3.0	3.1	3.1	3.1	3.1	3.0
Being part of something important	3.0	3.2	3.0	3.1	2.8	3.0	3.0
Receiving discounts for green products	2.9	3.1	2.8	2.9	2.8	2.9	2.7
Having fun	2.8	3.1	2.7	2.8	2.8	3.0	2.7
Living in a "Cool California City"	2.8	2.7	2.7	2.9	2.6	2.9	2.7
Getting to know your neighbors	2.6	2.6	2.6	2.7	2.3	2.7	2.6
Making a political statement	2.4	2.4	2.4	2.5	2.3	2.4	2.5
Meeting like-minded people	2.4	2.5	2.3	2.5	2.2	2.5	2.4
Receiving recognition for your city	2.4	2.6	2.3	2.5	2.1	2.5	2.4
Winning prizes	2.1	2.5	2.0	2.1	2.0	2.3	1.9
N	318	47	259	195	106	110	137

Motivation	Climate change skeptics	Republicans & Conservatives	Democrats & Liberals	Less than 4-yr degree	Hold advanced degree	Earned no Points	Earned over 5k Points
Improving where you live	3.2	3.4	3.5	3.4	3.4	3.5	3.4
Making an environmental statement	2.6	2.6	3.4	3.0	3.3	3.2	3.2
Supporting organizations you care about	3.0	3.1	3.3	3.0	3.3	3.1	3.1
Learning how to save money	3.3	3.4	3.1	3.4	2.9	3.3	3.0
Learning about new technologies	3.0	3.0	3.1	3.0	3.1	3.1	3.0
Being part of something important	2.6	2.8	3.1	2.9	3.0	3.0	3.0
Receiving discounts for green products	2.7	2.9	2.9	3.0	2.6	3.1	2.6
Having fun	2.7	3.0	2.7	2.9	2.7	2.9	2.6
Living in a "Cool California City"	2.5	2.6	2.8	2.8	2.7	2.8	2.6
Getting to know your neighbors	2.4	2.8	2.6	2.6	2.6	2.6	2.5
Making a political statement	1.5	1.6	2.7	1.9	2.8	2.3	2.5
Meeting like-minded people	1.9	2.1	2.5	2.3	2.4	2.4	2.3
Receiving recognition for your city	2.1	2.2	2.4	2.4	2.3	2.4	2.4
Winning prizes	2.0	2.2	2.0	2.4	1.9	2.3	2.0
N	42	41	230	69	108	139	111

Figure 49. Motivations for Program Participation by Demographic Characteristics

Participants were also asked about their values, which are thought to filter how information is perceived and frequently trigger an emotional response when activated (Schwartz 1994). We used the consolidated Schwartz Values Survey (Lindeman and Verkasalo 2005), which includes a common list of universal values shared across cultures (see Appendix A.2 for a description of terms). Again, we see remarkable consistency between individuals, with universalism, self-direction, security and benevolence as the top values for all groups, except conservatives, for whom tradition is also a core value. Power was at the bottom of the list, followed by prestige and hedonism, although hedonism (described as seeking pleasure) was an important value for people under 35. It is noteworthy that while hedonism is often a strongly held value for youth, "having fun" was not a primary motivation for joining the Challenge, perhaps indicating that they felt the program would not really be fun (although they were still motivated for altruistic reasons). See Figure 50.

	KEY
Extremely important	7.0
very important	6.0
	5.0
	4.0
important	3.0
somewhat important	2.0
not very important	1.0
not at all important	-

Please rate how important each value below is as a guiding principle in your life.

Human Value	All Participants	Under 35	55 or older	Women	Men	Under $40k personal	Over $70k personal
Universalism	5.3	5.2	5.3	5.6	5.0	5.5	5.4
Self-direction	5.1	5.5	4.8	5.2	5.1	5.1	5.2
Security	5.1	5.5	4.9	5.3	5.0	4.9	5.1
Benevolence	5.1	5.1	5.0	5.3	4.9	5.4	5.0
Tradition	3.9	3.9	3.6	4.0	3.6	3.7	3.8
Achievement	3.5	3.7	3.0	3.5	3.3	3.2	3.8
Conformity	3.0	2.8	2.8	2.8	3.0	2.8	3.1
Hedonism	2.5	3.2	2.1	2.3	2.5	2.3	2.4
Prestige	2.4	2.7	2.1	2.1	2.3	2.4	2.4
Power	1.8	1.9	1.4	1.5	1.6	1.6	1.8

Human Value	Conservatives	Liberals	Less than 4-yr degree	Advanced degree	Earned no Points	Over 5k Points	All Participants
Universalism	4.1	5.7	5.0	5.7	5.5	5.1	5.3
Self-direction	5.0	5.2	5.0	5.4	5.2	5.0	5.1
Security	5.7	5.0	5.8	5.0	5.3	4.8	5.1
Benevolence	4.6	5.3	5.1	5.3	5.1	5.0	5.1
Tradition	4.5	3.9	4.4	3.6	4.3	3.3	3.9
Achievement	3.0	3.7	3.1	3.8	3.6	3.3	3.5
Conformity	2.9	2.9	3.7	2.7	3.2	2.4	3.0
Hedonism	2.4	2.5	2.8	2.4	2.5	2.3	2.5
Social Status & Prestige	1.9	2.5	2.4	2.3	2.4	2.1	2.4
Power	1.3	2.0	2.0	1.6	1.8	1.6	1.8

Figure 50. Human Values by Demographics and Points

6.3.4. Participant Evaluation Surveys

Six months following the end of the CoolCalifornia Challenge participants were asked to complete the research survey for a second time. A new section on program evaluation was added, which asked questions on participants' experience with the program and recommendations for further program development. The following is a brief summary of results.

Participants were asked, “In what ways, if any, has the program changed your opinions about climate change or energy efficiency?” While this question did not explicitly ask about what actions participants had taken because of the program, ten respondents volunteered this information anyway, including: changing light bulbs, water heater, furnace, AC, solar panels, water tolerant plants, smart thermostats, new appliances, attic insulation, drying clothes on the line, and reducing idling. No one suggested that the program had changed his or her opinions of climate change or energy efficiency.

Over 70% of respondents rated the program as either Excellent or Good, while 20% rate the program as Fair and 7% rated the program as Poor or Fail (Figure 51). Opinions on the program website rated only slightly lower than the program overall, while less than 50% of respondents rated the program newsletters favorably. A large portion of participants either did not have communication with local program implementers or rated that communication as only fair.

Most respondents who rated the program unfavorably noted difficulty and frustration using the software. Several respondents said that they had problems inputting data and gave up. While the program did receive over 10,000 successful individual energy and vehicle reports, some users found the process to enter the data cumbersome, “clunky” or simply too difficult. A number of respondents requested that data be linked directly from utilities. Several also noted that they did not remember receiving newsletters or communication from the program, which may in fact have been the case since certain email providers frequently blocked email from the Challenge software.

The most common recommendations to improve the program were to make the program “easy and fun.” Several subjects wanted more personalized attention, including more community events, local stories, local communication and guidance. A number asked for simple, small daily or weekly challenges or tasks to keep people engaged. In contrast, others noted that the program should focus more on “fundamental change” with drastically different technologies, policies and lifestyle choices. As one participant noted, “you use the ‘simple ways to save the planet’ model. It isn’t simple.” Still others wanted very specific actions to be promoted, like cleaning solar panels or planting shade trees. One participant noted that the program should engage elementary schoolchildren. The diversity of these comments underscores the difficulty of trying to meet needs of a large range of stakeholders and population segments. It is impossible to please everyone. At the same time, the comments were extremely helpful to understand the diversity of needs and ideas to improve the program.

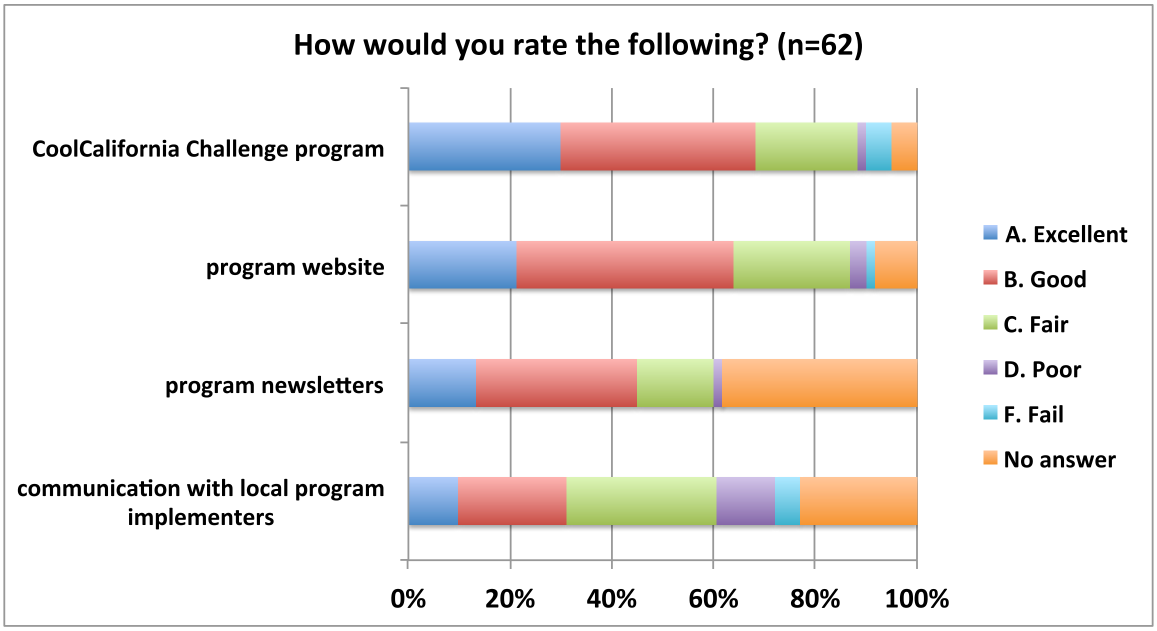


Figure 51. Participant Evaluation Survey Results: Project Ratings

6.3.5. Interviews with City Program Managers

The research team conducted interviews with six city program managers from four of the eight participating cities: Chula Vista, Davis, Sacramento and Tracy. City program managers from non-finalist cities did not complete the consent form to participate in the interviews. Subjects were asked questions on their city's original motivation for joining the Challenge, their goals and expectations and the extent to which those expectations were met, the resources contributed locally to run the program, the strategies employed, project outputs and outcomes, as well as recommendations for future program developers (See Appendix A.4 for interview instrument). Below is a summary of findings from transcriptions of those interviews.

All participating cites, including those not interviewed, had recently completed climate action plans. While community engagement was frequently mentioned in these plans, they typically did not include specific recommendations or programs. Cities were largely interested in the Challenge as a way to fill this need. Even though the Challenge was marketed as a "pilot program" there was some expectation that it would be more fully developed and that cities would simply need to recruit participants. Some of the cities already had fairly robust community engagement programs, particularly Davis and Chula Vista, yet other cities were just starting their community engagement on climate and energy. Davis, the winning city, has a 30+ year history of community engagement on energy and the environment, and the Cool Davis program was created specifically to engage Davis residents and businesses in climate action. Similarly, the city of Chula Vista was one of the first cities to create a climate action plan and the local utility (SDG&E) funds city staff to design and implement community-scale energy efficiency campaigns. Still, other less experienced cities, such as Tracy, were able to perform extremely well in the program by investing considerable staff and volunteer time to engage community members. While experience and technical capacity of city program managers and core volunteers varied somewhat between cities, it was the dedication of staff and volunteers to the program, and not their experience, that seemed to be the most critical factor.

As the front line of engagement with participants, the city program managers were the first to receive program feedback. All of the city program managers mentioned some level of disappointment and frustration with the slow pace of software development. According to one subject, by the end of the program the software was at about "80%" of where they would have liked to be at the start of the program; had the program started at 80%, the program would have been much better. Some of the cities noted that they initially did not realize how much staff and volunteer time would be required of them to make the program a success in their community, while another noted that they really did not have specific expectations but became heavily involved during months of intense competition. All cities noted that more financial support would have been helpful, but this ranged form a few thousand dollars to tens of thousands.

City program managers offered a number of suggestions. Common suggestions included more robust software and more support to city program staff and volunteers, either in-kind contributions or through additional funding. One of the cities stressed the importance of retaining complete contact information of participants during and after the program (cities were able to contact participants during the program via the software, but did not have direct access to their contact information). There was general agreement that the program should be well-planned in advance, giving cities sufficient time to prepare their strategies, and that the program and software should not change substantially during the program itself. All cities agreed that the program was too long and suggested a shorter campaign of between 4-9 months. While some liked the idea of targeting specific populations, particularly schools, they stressed the importance of having fully developed programs and long lead times to reduce barriers and make the program easier to implement.

Despite the fact that non-finalist cities did not participate in the interviews, it was clear from conversations during the program that motivation was low for cities that did not perform as well as the top cities. In some cases, city governments, including mayors, made personal appeals to motivate residents and there was some amount of embarrassment when cities did not perform well. An important lesson from this experience was that all cities should receive benefits from future programs, regardless of their ranking.

6.3.6. Research Hypotheses

This study was primarily exploratory and descriptive research, rather than theory-driven work designed to test an explicit hypothesis. Nonetheless, a number of operating hypotheses were tested, some of which were identified in the original research contract, and others that were added. A summary of hypotheses and results is presented in Appendix A.6. The most relevant study results are presented above and discussed below.

6.4. Discussion

Energy and GHG Savings

Participants tracking electricity saved an average of 14% compared to a control group, while no discernible savings were measured for natural gas. There are several plausible explanations for this difference. First, participation in the Challenge was greatly increased only during the most intense months of competition during the Qualifying Round (May through July, 2012) and the end of the Finalists Round (April through May, 2013) when there is much less demand (and opportunity to reduce) space and water heating. Electricity also supplies a larger number of end uses that may be easier to reduce through conservation than natural gas, which is primarily for space heating, water heating and cooking. For greenhouse gas reductions, lack of natural gas savings is particularly problematic since electricity is becoming less carbon intensive over time and will soon become a much smaller source of GHG emissions than natural gas for most California homes. A more targeted approach to identify and overcome barriers to adoption of natural gas conservation measures, applying competition strategies to motivate natural gas savings (e.g., a natural gas reduction goal and recognition for households meeting the goal) and shifting the timeline of the program to encourage more participation in winter months may be expected to lead to natural gas savings for future programs.

This study calculated savings of 183 MWh of electricity, equivalent to the average annual electricity consumption of 23 California homes and 50 metric tons of CO_2; however, this does not include any potential savings from motor vehicles (which were not calculated in this report due to reporting errors) or potential savings from households when not reporting electricity. Using an alternative methodology to calculate “bonus points” based on changes in participants’ past reported performance total savings were around 225 metric tons of CO_2, but this still does not include potential savings from household when not reporting. This large range of potential savings (50 to potentially over 225 metric tons of CO_2) highlights the challenge of quantifying results from opt in household greenhouse gas reduction programs.

Survey Results

Challenge participants were well represented across income brackets, but were primarily highly educated, politically liberal and middle-aged, with strong pre-existing pro-environmental attitudes and practices. Using the Opinion Dynamics population segmentation nomenclature, roughly 70% of active participants were “leading achievers,” 20% were “striving believers” and 10% were “practical spenders.” Young people were much less likely to enroll and to actively participate and earn points in the program, suggesting that future program interventions would need to be much more highly tailored to their needs in order to earn their engagement. While conservatives and “practical spenders” were less likely to enroll in the program, those who did performed well compared to more liberal counterparts. Education was an important factor; participants with advanced degrees earned two to three times more points than participants without a college degree. Considerable effort would be needed to actively engage populations with less formal education. The most active participants were “leading achievers” and “practical spenders,” with “striving believers” straggling behind on points per household.

Households reported very altruistic and intrinsic motivations for participating in the program, with helping their community, making an environmental statement and supporting organizations they care about topping the list of motivations. Their values were also very much aligned with protecting the environment (universalism) and improving their communities (benevolence), regardless of political orientation or demographic characteristics.

Even though participants already had strong intrinsic motivation and largely led low carbon lifestyles, they demonstrated strong capacity to make further reductions during the program. Participants were most actively engaged in the program during the most intensive months of competition (summer 2012 and spring 2013), suggesting that competition is a useful strategy to catalyze participation and engagement.

Due to the small number of participants completing the survey during the program and 6-months post, and limited self-reported energy readings after completion of the program, we were not able to estimate persistence of behaviors or energy savings after completion of the program. Future program iterations could collect data directly from utilities, with permission from participants, in order to better evaluate persistence of behaviors and energy savings over time.

Participant Evaluation Survey Questions & Program Manager Exit Interviews

Participant survey data and interviews with program managers were helpful to understand what worked well and what elements of the program need improvement.

Participant approval ratings for the program (70% excellent or good, and 90% fair or better) were somewhat higher than expected given the pilot nature of the program and emerging software capabilities. A number of participants noted changes in behaviors and energy efficient equipment purchases that were at least in part due to the program.

While a number of participants expressed difficulties using the software, participants did successfully enter over 10,000 energy, motor vehicle or Kudo Points reports during the program, serving the primary purpose of the program well. By the end of the program the software had become quite sophisticated, providing feedback to participants entering data and facilitating communication with participants.

Local program managers, as well as program staff and researchers, provided a number of recommendations for future program development. A few of the most important recommendations are:

- Future programs should seek to increase motivation for all cities, even those not directly contending for top honors.
- Care should be taken to design programs to meet a wide range of needs from communities with different levels of capacity and diverse populations.

- In its current form the program has not able to successfully engage younger and less households. Future programs should develop targeted programs at youth and young adults living in shared housing to engage them more actively in the program.
- Programs should experimentally test different messages and intervention strategies to see which are more effective.
- Implementation of all community-based social marketing steps proved too time consuming for cities with limited program implementation capacity. Future programs should focus on a few behaviors common to all cities and develop program intervention that are tightly integrated with the statewide program rather than relying on each city to develop its own unique interventions. Interventions should be crafted following steps of community-based social marketing to select behaviors, identify barriers and motivations, use appropriate intervention strategies to highlight motivations and reduce barriers, test and disseminate.
- The length of the program should be shortened to prevent program fatigue from city program managers and participants. One tradeoff is a program covering summer months will have less opportunity for natural gas savings, while a winter program would have less opportunity for electricity savings and highlighting biking or outdoor activities and events.
- Additional funding or incentives would be required to engage communities more deeply in the program.
- The program software should be fully developed, engaging and easy to use.

6.5. Conclusion

The purpose of this study was to design, implement and evaluate an energy and carbon footprint reduction competition between residents of California cities. Program participants demonstrated higher than expected levels of participation and reductions in electricity consumption and greenhouse gas emissions during the program's pilot year. The program successfully engaged nearly 3,000 participants in 8 participating cities over the 13-month program, with 900 participants submitting over 10,000 monthly electricity, natural gas and motor vehicle reports.

The program appealed primarily to older, highly educated, more politically liberal households, although conservatives were also engaged and earned nearly as many points per household. Despite strong pre-existing intrinsic motivation to engage in low carbon practices, participants demonstrated capacity to make further reductions through their participation in the program.

Challenge participants saved an estimated 14% in electricity for those actively entering energy data in the software, which is encouraging given the pilot nature of the program. Future efforts could potentially expand these savings to a wider audience and achieve improved results.

The program did not result in measurable savings in natural gas. One possible explanation is the relatively low level of participation in the program (measured by new registrations and energy readings) during winter months when there were no deadlines or specific program objectives for participants or cities. Participants also tracked, and were encouraged to reduce motor vehicle usage; however, due to suspected reporting errors it was not possible to estimate reductions in vehicle travel or transportation greenhouse gas savings.

The element of competition proved to be a powerful motivator, with participation levels spiking only during moments of intense competition at the end of the Qualifying and Finalists rounds. One drawback of the competition model was cities that were not in contention for a finalist spot or winning the program had less motivation to engage in the program. Future program models should seek to increase motivation for all cities, even those not directly contending for top honors, and care should be taken to design programs to meet a wide range of needs from communities with different levels of capacity and diverse populations.

Chapter 7. Conclusion

The primary goals of this dissertation were to quantify consumption-based greenhouse gas emissions and reduction opportunities for U.S. households and communities and to investigate the potential of an inter-community GHG reduction competition among residents in California cities. These two goals suggest the potential for a new kind of urban planning that prioritizes GHG mitigation opportunities in each location and engages community members directly in the adoption of low carbon technologies and practices. Such initiatives are intended to compliment top-down climate policy, e.g., national market-based polices such as carbon taxes and cap-and-trade, and non-market policies including standards and regulation. Several findings are salient to scaling up community and regional scale climate mitigation.

The first major finding was quantification of household and community carbon footprints and GHG mitigation opportunities for metropolitan areas (Chapter 3) and for essentially every U.S. zip code, city, county and state (Chapter 4). The results reveal important differences in the size and composition of household carbon footprints as well as in the GHG reduction potential and financial cost of mitigation in different locations. For example, residential electricity accounts for only roughly five percent of average household carbon footprints in California but 30% in some U.S. locations, while transportation is a larger contributor to GHG emissions in California than most other states. Lack of information on these differences may be contributing to misallocation of resources to address household impacts on climate change. For example, in California a far disproportionate share of funding is directed at reducing consumption of residential electricity compared to other sources of household carbon footprints.

Carbon footprints also vary considerably within urbanized areas, with income, size of homes and distance to urban core contributing greatly to carbon footprints and the opportunities to reduce them. Despite these differences, Chapter 3 shows that lowering household greenhouse gas emissions, through shifting consumption to be less carbon intensive products, can result in significant financial savings for all household types and locations. The average U.S. household, for example, would save enough money by shifting consumption patterns to be able to purchase sufficient carbon offsets to become completely carbon neutral.

In part to address a clear information barrier, this study developed online carbon management software and interactive maps allowing users to quickly identify GHG hotspots, compare their carbon footprints to similar users (comparative feedback) and prioritize GHG mitigation opportunities for each location and household. The data suggest the importance of targeting policies and programs addressing household consumption to the most carbon-intensive activities in each location and for different population segments within locations.

7.1. Implications for Urban and Regional Planning

The purpose of the study in Chapter four was two-fold: a) to develop household carbon profiles of each zip code, city, county and U.S. State, and b) to analyze the effect of population density and level of urbanization on full life cycle greenhouse gas emissions. The work is also intended to help cities better understand the primary drivers of household carbon footprints in each location, to present in a visually striking way the impacts and interactions of our energy, transportation, land use, shopping and other choices, and to motivate cities to use this information to begin to create highly tailored climate action plans for their communities

Previous studies have considered only a relatively small number of case studies of urbanized carbon footprints. Most studies have only considered partial household GHG impacts, e.g., vehicle fuel consumption and household energy. Similarly, most other similar studies have tended to address one spatial scale (e.g., metropolitan areas, or cities) and not multiple spatial scales. This is the first study of household carbon footprints to include every U.S. location, including essentially all zip codes, cities, counties and metropolitan areas. It one of the first, and the most geographically comprehensive, studies to compare population density with full life cycle greenhouse gas emissions. It is also one of the first studies to evaluate household carbon footprints at multiple spatial scales (zip codes, cities, counties, metropolitan areas).

Several of the findings confirm previously know relationships. First, there is a strong correlation between population density and average household carbon footprints of large central cities ($r^2 = 0.3$). Second, the primary drivers of carbon footprints are household income, vehicle ownership and home size, all of which are considerably higher in suburbs. Other important factors include population density, the carbon intensity of electricity production, energy prices and weather. The model includes 37 local variables in total. The study also confirms that central cites and suburbs have important social, economic and environmental interdependencies

There are also a number of new findings that are potentially relevant to future city planning.

a) Population dense central cities have significantly lower carbon footprints than less dense central cites; however, these cities also have more extensive suburbs. When considering the net effect of all metropolitan residents (suburbs and central city residents together), larger, more populous and population-dense metropolitan areas have slightly higher average carbon footprints than less populous and lower population-dense metropolitan areas. This is this is the primary finding of the paper that is used in the title. The implication for policy is that suburban sprawl undermines, or cancels, the benefits of urban population density. Urban development planning should focus on impacts at metropolitan as well as more local scales, as is typical in regional transportation planning.

b) There is <u>no correlation</u> between population density and average household carbon footprints of zip codes (Figure 15a), cities (Figure 15b), counties (Figure 15c), or metropolitan areas (Figure 15d)...adjusted r^2 for all of these locations is <0.01. This is consistent with other recent research showing there is a huge range of household greenhouse gas emissions at any given population density. It would be incorrect to say population density is correlated with lower household carbon footprints.

c) There is <u>no correlation</u> between population density and average household carbon footprints of suburbs (adjusted r-squared = 0.006). See 20, model 2. There is a correlation for central cities, but there is not a correlation for suburbs. Suburbs are different. The next two points explain how.

d) When classifying suburbs into low, medium and high population, more populous and population dense suburbs have higher HCF, not lower. Large suburbs have population densities 3 times larger than mid-sized suburbs, and 6% higher carbon footprints. See Table 18. This is largely because more population dense suburbs have higher incomes than less dense suburbs. Higher incomes translate to important social, cultural and economic benefits, but higher incomes also generally correspond with higher consumption and greenhouse gas emissions.

e) When controlling for income and household size, there is a fairly strong correlation between population density and HCF in central cities (r^2=0.32), suburbs (r^2=0.30) and all cities (r^2=0.30). If policies can control for income, or even encourage lower income infill, then population density has a strong potential impact on lowering greenhouse gas emissions of those locations. In central cities, population density lowers carbon footprints, regardless of income, although the benefits are higher with low-income densities. In suburbs (which account for nearly 50% of the U.S. population), increasing population density has lead to higher incomes, and thus higher consumption, while not reducing vehicle emissions sufficiently since people still travel long distances to reach central cities, or to travel within large suburban areas.

f) There is an inverted-U relationship between population density and HCF; HCF increases at from low to medium population densities, and decreases from medium to high population densities. The turning point is about 3,000 persons per square mile, which is very close to median population density of all locations, and a little higher than the population density of larger suburbs (which have densities of 2,700 persons per square mile). This helps explain why larger suburbs have higher carbon footprints; they are located to the left of the inflection point, while less dense suburbs are even further left on the x-axis. See Figure 15.

This dissertation suggest different implications for suburbs and for central cities. Below is a line-by-line summary of the paragraph in the Discussion section describing potential implications for urban planning. Note: these are not findings, but comments by the authors to generate policy discussion and future research.

a) *As a policy measure to reduce GHG emissions, increasing population density appears to have severe limitations and unexpected trade-offs.* Our primary conclusion is the population density has contributed to lower household carbon footprints in urban core cities, but low carbon central cities also tend to have high carbon footprint suburbs. Planners need to consider economic, social and environmental interrelationships between central cities and suburbs in planning more sustainable communities. The data show the effect of existing population density on existing urban infrastructure and household carbon footprints. Our data does not suggest how HCF changes over time as population density changes over time so our comments are somewhat speculative here based on past historical data. To the extent that the future policies look like the past policies, the limitations and tradeoffs we suggest may be valid and worth considering in future planning.

b) *In suburbs, we find more population-dense suburbs actually have noticeably higher HCF, largely because of income effects.* This is one of the most surprising findings that has been missed in previous research that has explored only a limited number of (mainly central) cities, or large metropolitan areas. This finding is relevant to 50% of the U.S. population living in U.S. suburbs. The implication is suburbs should be treated differently than central cities.

c) *Population density does correlate with lower HCF when controlling for income and household size; however, in practice population density measures may have little control over income of residents.* <u>This statement is in reference to suburbs only and should not be taken out of context</u>. Population density correlates with lower HCF regardless of income in central cities. In suburbs, however, we have historically seen that more population dense cities have higher incomes, and higher carbon footprints. Cities seeking to reduce community-wide greenhouse gas emissions from a lifecycle perspective may want to consider ensuring sufficient low income and middle-income infill housing is built.

d) *Increasing rents would also likely further contribute to pressures to suburbanize the suburbs, leading to a possible net increase in emissions.* <u>This statement is in reference to higher incomes in suburbs and not a statement about population density and rents generally; it should not be taken out of context.</u> Increasing housing stock should generally decrease rents, not increase rents, by decreasing demand for housing. Higher incomes, on the other hand, should increase property values and rents. While it may be possible that a focus on multi-unit housing in city cores could increase property values and rents for more spacious, single-family homes, this is not a point we make in the paper. More research is needed on this important question.

e) *As policy measure for urban cores, any such strategy should consider the larger impact on surrounding areas, not just the residents of population dense communities themselves.* Transportation planning is frequently done at a regional level. A good example of this is California's SB375, which encourages regional targets and plans to lower greenhouse gas emissions from transportation. City planners; however, are primarily concerned with reducing emissions from their own jurisdictions and may not be concerned with impacts outside of their jurisdictions. This comment is very consistent with "smart growth" ideology and policies that seek to take a more holistic view of social, economic and environmental impacts of growth.

f) *The relationship [between population density of urban cores and HCF] is also log-linear, with a 10-fold increase in population density yielding only a 25% decrease in HCF.* This is a factual statement of our results. We chose a 10-fold increase as the example, because it shows the full range of our results in the fewest words. A doubling of population density from 5,000 persons to 10,000 persons per square mile would have been a more realistic example. This corresponds to about a 5% decrease HCF, based on current data. Our intention was to show the limitations of density in reducing global greenhouse gas emissions. The U.S. emits five times the global average per capita emissions and globally humanity needs to reduce emissions by 80%, so planners should arguably be thinking about how to achieve a 10- to 20-fold decrease in emissions. Given limited technical capacity in cities, we suggest that population density has limited potential and call for more tailored solutions, which in our view are urgently needed.

g) *Generally, we find no evidence for net GHG benefits of population density in urban cores or suburbs when considering effects on entire metropolitan areas.* This statement is in reference to impacts of population density on entire metropolitan regions, not cities; it should not be taken out of context. A better, and certainly less controversial way of stating this would be that density does have positive effects on reducing emissions in urban cores, but these gains are undercut by income and urban form within large metropolitan areas. One of the most alarming findings, in terms of planning is that metropolitan regions all have very similar household carbon footprints when you consider the net impacts of residents of urban cores and suburbs together. Worse still, we find larger, more population dense metropolitan areas have slightly higher HCF.

The paper suggests "an entirely new approach of highly tailored, community-scale carbon management is urgently needed." We recommend that cities understand the size and composition of household carbon footprints in their locations and then develop customized plans that address the largest opportunities to reduce those impacts. Until now, cities and counties have lacked a way to estimate total household carbon footprint in their jurisdictions without paying for expensive and time-consuming studies. We hope municipalities will use the benchmarking carbon footprint profiles and data in this study to aid in this process.

The study also has several limitations. First, the CoolClimate estimate should be considered benchmarks. We do not measure consumption or emissions, but rather estimate consumption of energy, transportation, food, goods and services based on locally-available data (37 variables in total, the most important of which are vehicle ownership, income, household size, population density, energy and fuel prices, the carbon-intensity of electricity and weather). Second, we assume a linear relationship between expenditures and emissions for goods and services. This is consistent with all similar studies on household carbon footprints. Unlike most such studies, we do not assume a linear relationship between income and food consumption; we have previously shown that while higher income households spend more on food, they do not eat more of any category of food than lower income households. Similarly, we know upper income households spend more on alcohol, but this does not mean that they drink more; rather they drink more expensive alcohol. Third, our model tends to underestimate consumption (and therefore emissions) at high or low levels of transportation and household energy. This is the nature of using multivariate regression analysis. See the Chapter 4 for more discussion on limitations and model validation.

Population density has drawn considerable attention and influence in urban planning, yet there is increasing evidence that this is a poor sustainability strategy in certain locations. Increasing the number of large homes in low-density suburbs, i.e., making them somewhat more compact, would almost certainly increase net GHG emissions compared with increasing home construction in urban cores. In the first analysis of population density across all U.S. locations, Chapter 4 demonstrates that more population dense suburbs actually have higher household carbon footprints. In essence, unless shorter driving distances and smaller homes accompany population density, there is no apparent GHG benefit to density. Yet large homes, packed tightly into small lots, located far from centers of urban cores aptly characterizes much of California's recent housing development. This sort of density increases resource consumption and emissions locally, and regionally. Adding density to urban cores, on the other hand, dramatically decreases net emissions if sprawl can simultaneously be contained. Population density, of course, is only one factor in smart growth strategies. Other strategies are very consistent with our concept of tailored solutions, including increasing access to public transit, making cities more pedestrian and cycle friendly, colocation of housing with jobs, entertainment and shopping, and other smart growth policies.

7.2. Implications for Behavior Change Policy

Information technologies alone may have limited impact without programs actively engaged to use them. While our carbon footprint calculator has been widely used[4] its impact may be limited to those who are motivated enough to find and use the tool, to the extent that they understand and trust the information, and that it tells them something they didn't already know about a decision that they are likely to make. Such tools are also unlikely to improve the intrinsic motivation of individuals to take action. When targeting households it is also important to consider local values, competing priorities, barriers, motivations and abilities of population segments. Local community program developers are well-positioned to understand these local factors and to use social norms, public commitments, recognition, prompts, advising, persuasive messaging and other strategies known to influence human behavior.

The goal of the CoolCalifornia Challenge was to design, implement and evaluate a carbon footprint reduction competition between participating California cities. The program mobilized city staff and volunteers in each community to engage residents on climate change and encourage them to track their electricity, natural gas and motor vehicle usages in online software. Participants earned points for having lower emissions than similar households in their location (using the CoolClimate Calculator benchmarking methodology described in chapters 3 and 4), and triple-rated points for reducing their consumption over time. They also earned points for taking small actions such as uploading stories and photos, inviting friends and taking a research survey.

The program used techniques common to behavioral interventions, including commitments, goal setting, feedback, local messengers, social networks, persuasive messaging, incentives and competition to recruit and engage households in a yearlong program. Participants earned points for tracking and reducing household energy consumption and motor vehicle emissions, as well as for taking simple one-time actions, like inviting friends, uploading stories and completing a research survey.

[4] The CoolClimate Calculator (coolclimate.berkeley.edu/carboncalculator) has received well over one million unique visits over the last nine years. Versions of the tool have been adopted by the states of California (CoolCalifornia.org/calculator) and Oregon (http://www.deq.state.or.us/programs/sustainability/carboncalculator.htm), as well as a number of companies and organizations.

Participating cities enrolled 2,667 households and logged over 10,000 electricity, natural gas and motor vehicle odometer readings in the online software. Using in Variability in Adoption (VIA) methodology, participants reduced electricity consumption by 14%, but no savings in natural gas. Lack of natural gas savings is possibly due to lack of competition deadlines during winter months when opportunities to reduce natural gas are higher, and fewer natural gas end uses for potential reductions. Due to participant user error we were not able to estimate savings from motor vehicles.

Older and more highly educated participants outperformed younger and less educated participants, while income, political identity and attitudes toward climate change affected participation levels, but not performance. Participants reported very altruistic motivations for joining the program, including improving where they live, protecting the environment and helping organizations they care about. While winning prizes and earning recognition for their city ranked low on a list of reported motivations, participation in the program dramatically spiked only during intense moments of competition.

Much of the research conducted for this study was descriptive in nature, with the CoolCalifornia Challenge serving as a case study. Since it was not possible to run a randomized controlled trial, we were not able to rigorously test hypotheses. A summary of hypotheses tested and their results is included in Appendix C.6. Nonetheless, the program does serve as a proof of concept that inter-city competition may serve as a mechanism to scale up the adoption of low carbon technologies and practices across a wide of cities and demographics. As of this writing, the second year of the program is now complete. It achieved roughly a 40% increase in participation, a 60% increase in GHG savings in half the time (6 months) and with less than half the cost.

Together, this evidence suggests that inter-city competitions can be a successful strategy to reduce community-wide greenhouse gas emissions. The program not only provides information to residents, but seeks to increase their motivation, capacity and belief in their ability to create meaningful change. The communities that achieved high levels of sort of engagement were the most successful in the program.

7.3. Future Work

A number of projects are currently under development that build upon work presented in this dissertation. The first task is to develop higher spatial resolution maps, down to neighborhood scales. This resource will help communities target different mitigation actions to different neighborhoods, but also provide better benchmarking for households to compare their own emissions at neighborhood scales. For example, we estimated average vehicle miles traveled for the city of Davis California at the level of U.S. Census Tracks (Figure 52). This map shows that the neighborhoods that have been developed over the last 20-30 years have the highest average per capita vehicle usage. Additionally, these neighborhoods commute almost exclusively by car, whereas in other neighborhoods, biking, walking and public transit are primary commute modes. This suggests a targeted approach to community-based transportation programs, focusing on promoting adoption of electric and efficient vehicle technologies in high VMT neighborhoods.

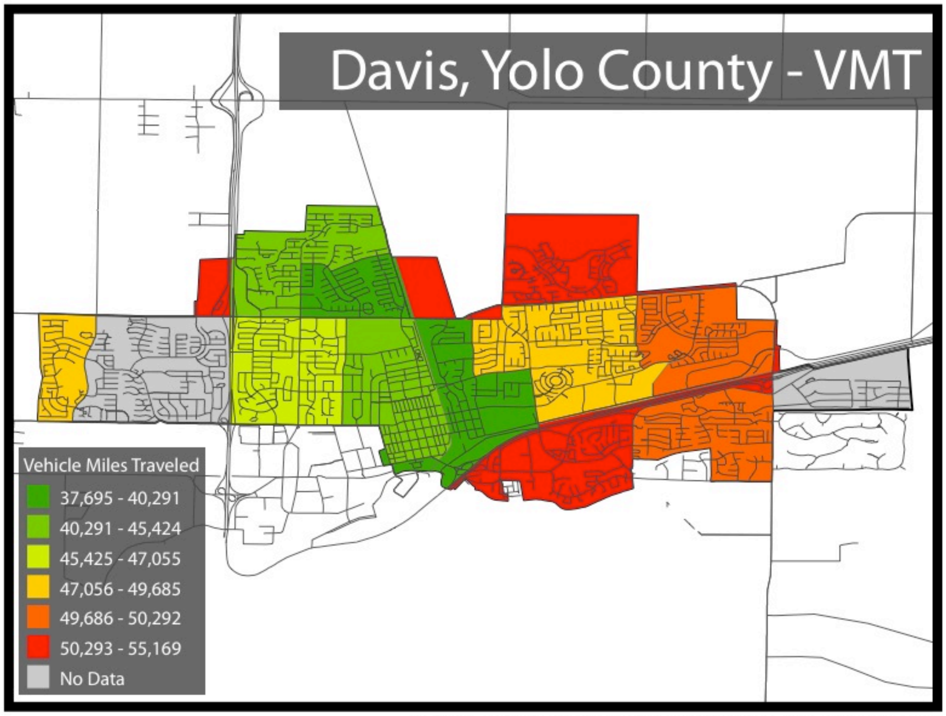


Figure 52. Average household vehicle miles traveled (VMT) in Davis, California

The next step will be to add temporal data to track changes in carbon footprints over time in each location and compare the effect of different polices (e.g., land use policy). For example, demonstrating that all of the red and orange areas of the VMT map of Davis were mostly developed during the last 20 years could influence future planning priorities. Temporal data would show clearly show the effect of previous land use decisions.

Ultimately, the goal of this work will be to create an ecosystem "smart" decision-support tools for U.S. and international communities that help identify the largest opportunities to reduce GHG emissions, provide comparative feedback and access to programs that enable the adoption of low carbon technologies and practices at a wider scale. This will involve creating tools and programs that are participatory in nature, that effectively utilize resources, build local technical capacity and match with the values, goals, priorities, abilities and motivations of local communities. If local climate action plans are to achieve their full potential they must become mechanisms that enable broad social and institutional change at household, community and regional scales.

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Appendix A: Supporting Materials for Chapter 5 – CoolCalifornia Challenge

Appendix A.1. Summary of key progress indicators and electricity data by city

This appendix contains key progress indicators for cities participating on the CoolCalifornia City Challenge pilot program (2012-2013). Table 1 presents key indicators for each participating city. Green, yellow and red colors indicate first, second and third place rankings, respectively, among the top three cities for each indicator.

Table. Summary of Key Progress Indicators by City

City	Total Green Points	Avg Green Pts / HH	Green points per reporting hh	Total Bonus Points	Avg Bonus Pts / HH	Bonus pts per active household	Total Kudos Points	Avg Kudos Pts / HH	Kudo Pts per active hh	Total Points	Avg Pts / HH	pts per active hh
Davis	1,206,726	2,749	7,057	388,686	885	2,273	120,835	275	707	1,716,247	3,909	10,037
Chula Vista	1,065,155	1,553	5,885	399,543	582	2,207	98,054	143	542	1,562,752	2,278	8,634
Tracy	663,382	1,741	5,183	227,086	596	1,774	66,441	174	519	956,909	2,512	7,476
Sacramento	203,593	676	1,697	83,989	279	700	51,467	171	429	339,049	1,126	2,825
Citrus Heigh	60,498	455	1,407	49,948	376	1,162	25,400	191	591	135,846	1,021	3,159
Pleasanton	76,380	455	1,736	28,457	169	647	29,969	178	681	134,806	802	3,064
Pittsburg	82,583	810	2,503	49,505	485	1,500	9,199	90	279	122,889	1,205	3,724
San Jose	496,707	1,177	2,208	256,202	607	1,139	42,200	100	188	1,219,082	2,889	5,418
Santa Cruz	1,709	285	1,709	216	36	216	670	112	670	2,595	433	2,595
Total	3,856,733	1,462	4,077	1,483,632	562	1,568	444,235	168	470	6,190,175	2,347	6,544

Participants in the city of San Jose used proprietary software (Wattzon), while participants in all other cities used the Challenge software. There were several important differences between the two platforms. Most importantly, Wattzon connects to PG&E accounts directly so participants do not need to enter monthly energy data manually as in the Challenge software. This means that San Jose participants earned points every month regardless of their engagement with the software. At the same time, San Jose participants did not have the option to track automobiles. Given these differences in data collection, results for San Jose are not directly comparable to other cities.

Table. Electricity Mean, Standard Deviation and N of Treatment Group by City

MEAN

City	Mar-12	Apr-12	May-12	Jun-12	Jul-12	Aug-12	Sep-12	Oct-12	Nov-12	Dec-12	Jan-13	Feb-13	Mar-13	Apr-13
Chula Vista	297	220	293	328	335	438	393	378	359	446	449	330	326	265
Davis	425	257	325	348	385	431	357	354	356	453	460	360	338	278
Sacramento	340	287	303	370	372	478	371	309	360	427	433	359	340	279
Tracy	428	399	396	472	389	459	400	388	378	469	457	387	373	325
Other City	290	297	348	358	397	481	416	369	370	469	457	394	383	322
Total	366	300	332	374	372	452	384	366	363	454	454	358	344	283

STANDARD DEVIATION

City	Mar-12	Apr-12	May-12	Jun-12	Jul-12	Aug-12	Sep-12	Oct-12	Nov-12	Dec-12	Jan-13	Feb-13	Mar-13	Apr-13
Chula Vista	227	228	247	303	302	373	313	255	211	312	296	237	219	215
Davis	254	219	423	363	400	414	360	258	217	264	277	269	373	406
Sacramento	223	250	256	256	299	293	241	161	244	394	348	233	219	157
Tracy	233	230	242	330	346	393	385	388	296	302	297	280	360	395
Other City	288	284	211	255	280	262	193	146	160	200	175	211	304	421
Total	249	248	311	312	331	364	327	277	229	287	279	251	310	335

COUNT (N)

City	Mar-12	Apr-12	May-12	Jun-12	Jul-12	Aug-12	Sep-12	Oct-12	Nov-12	Dec-12	Jan-13	Feb-13	Mar-13	Apr-13
Chula Vista	160	160	160	160	160	160	160	160	160	160	160	160	160	160
Davis	150	150	150	150	150	150	150	150	150	150	150	150	150	150
Sacramento	112	112	112	112	112	112	112	112	112	112	112	112	112	112
Tracy	122	122	122	122	122	122	122	122	122	122	122	122	122	122
Other City	117	117	117	117	117	117	117	117	117	117	117	117	117	117
Total	661	661	661	661	661	661	661	661	661	661	661	661	661	661

Tabl. Electricity Mean, Standard Deviation and N of Control Group by City

MEAN

City	Mar-12	Apr-12	May-12	Jun-12	Jul-12	Aug-12	Sep-12	Oct-12	Nov-12	Dec-12	Jan-13	Feb-13	Mar-13	Apr-13
Chula Vista	351	343	334	408	550	540	438	363	400	542	484	477	446	391
Davis	298	352	325	484	462	813	724	534	554	682	495	484	439	302
Sacramento	350	365	350	413	478	487	484	444	435	884	653	457	690	537
Tracy	296	295	272	299	474	620	629	100	53	N/A	N/A	276	646	249
Other City	373	339	281	450	430	N/A	N/A	N/A	N/A	N/A	N/A	215	N/A	N/A
Total	331	338	312	393	503	581	506	381	421	591	495	455	466	358

STANDARD DEVIATION

City	Mar-12	Apr-12	May-12	Jun-12	Jul-12	Aug-12	Sep-12	Oct-12	Nov-12	Dec-12	Jan-13	Feb-13	Mar-13	Apr-13
Chula Vista	198	199	200	288	303	297	266	185	171	164	128	226	197	193
Davis	330	304	372	752	360	586	770	611	447	424	408	292	332	245
Sacramento	222	274	204	391	236	534	332	435	393	N/A	N/A	44	N/A	N/A
Tracy	213	245	269	336	352	394	560	157	N/A	N/A	N/A	N/A	N/A	N/A
Other City	383	209	403	271	236	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Total	286	246	279	390	310	418	424	297	259	256	245	224	248	207

COUNT (N)

City	Mar-12	Apr-12	May-12	Jun-12	Jul-12	Aug-12	Sep-12	Oct-12	Nov-12	Dec-12	Jan-13	Feb-13	Mar-13	Apr-13
Chula Vista	57	66	74	79	33	31	37	55	22	17	16	12	10	10
Davis	60	64	22	22	19	9	11	7	6	6	8	5	7	7
Sacramento	22	35	26	11	10	12	11	12	2	1	1	2	1	1
Tracy	46	52	48	48	10	7	3	3	1	0	0	1	1	1
Other City	49	60	34	20	3	0	0	0	0	0	0	1	0	0
Total	234	277	204	180	75	59	62	77	31	24	25	21	19	19

Appendix A.2. CoolCalifornia Challenge Participants Survey

Thank you for joining the CoolCalifornia Challenge and for agreeing to participate in this survey.

The purpose of the CoolCalifornia Challenge is to encourage Californians to adopt “greener,” more environmentally friendly lifestyles.

The following survey will aid the research team in understanding the motivations of CoolCalifornia Challenge participants in order to enhance the program and contribute to behavioral and social science research.

Completion of this survey is completely voluntary. You will receive points in the CoolCalifornia Challenge for completing the survey. You may choose to skip any question in the survey that you do not wish to answer by selecting “no answer."

Please answer the following questions to the best of your ability. Your answers will greatly increase the effectiveness of this program.

Part A. Demographics

1. How old are you?
18 to 24
25 to 34
35 to 44
45 to 54
55 to 64
65 to 74
75 or older
No answer

2. What is your sex?
Male
Female
No answer

3. What is your annual household income and personal income?

- Your household income?
    - Less than $10,000
    - $10,000 to $20,000
    - $20,000 to $30,000
    - $30,000 to $40,000
    - $40,000 to $50,000
    - $50,000 to $60,000
    - $60,000 to $70,000
    - $70,000 to $80,000

- $80,000 to $90,000
    - $90,000 to $100,000
    - $100,000 to $120,000
    - $120,000 to $150,000
    - Over $150,000
    - No answer
- Your personal income?
    - Less than $10,000
    - $10,000 to $20,000
    - $20,000 to $30,000
    - $30,000 to $40,000
    - $40,000 to $50,000
    - $50,000 to $60,000
    - $60,000 to $70,000
    - $70,000 to $80,000
    - $80,000 to $90,000
    - $90,000 to $100,000
    - $100,000 to $120,000
    - $120,000 to $150,000
    - Over $150,000
    - No answer

4. What is the highest level of education you have completed?
    - Less than high school
    - High school / GED
    - 2-year college degree (Associates)
    - 4-year college degree (B.A., B.S.)
    - Master (M.A., M.S., etc.)
    - Doctoral Ph.D.
    - Professional (M.D., J.D., etc.)
    - No answer

5. Generally speaking, do you think of yourself as politically conservative or liberal?
    - Conservative
    - Somewhat conservative
    - Neutral
    - Somewhat liberal
    - Liberal
    - No answer

6. Generally speaking, do you think of yourself as…
    - Republican
    - Democrat

- Other (please specify)
- No party / not interested in politics
- No answer

Part B. Lifestyle

7. How did you hear about the CoolCalifornia Challenge?
(check all that apply)

- A family member
- A friend
- A neighbor
- A colleague at work
- A classmate or teacher
- A contractor
- A community-based organization
- A community event or farmer's market
- A participant in the CoolCalifornia Challenge
- A public forum or meeting
- Television
- Radio
- Newspaper
- A flyer, brochure or poster
- Local government
- Someone came to my home

Other (please specify)

8. How often do you do the following?

- When the weather is nice outside, how often do you walk or bike instead of driving?
    - 5-7 days a week
    - 2-4 days a week
    - About once a week
    - Once or twice a month
    - Less than once a month
    - Never or rarely
    - No answer
- When the weather is not nice outside, how often do you walk or bike instead of driving?
    - 5-7 days a week
    - 2-4 days a week
    - About once a week
    - Once or twice a month
    - Less than once a month

    - Never or rarely
    - No answer
- Carpool instead of driving alone
    - 5-7 days a week
    - 2-4 days a week
    - About once a week
    - Once or twice a month
    - Less than once a month
    - Never or rarely
    - No answer
- Participate in a car share program
    - 5-7 days a week
    - 2-4 days a week
    - About once a week
    - Once or twice a month
    - Less than once a month
    - Never or rarely
    - No answer
- Recycle
    - 5-7 days a week
    - 2-4 days a week
    - About once a week
    - Once or twice a month
    - Less than once a month
    - Never or rarely
    - No answer
- Compost
    - 5-7 days a week
    - 2-4 days a week
    - About once a week
    - Once or twice a month
    - Less than once a month
    - Never or rarely
    - No answer
- Eat a vegetarian meal
    - 5-7 days a week
    - 2-4 days a week
    - About once a week
    - Once or twice a month
    - Less than once a month
    - Never or rarely
    - No answer
- Volunteer for a non-profit organization
    - 5-7 days a week
    - 2-4 days a week

- About once a week
- Once or twice a month
- Less than once a month
- Never or rarely
- No answer

- Attend educational events
  - 5-7 days a week
  - 2-4 days a week
  - About once a week
  - Once or twice a month
  - Less than once a month
  - Never or rarely
  - No answer
- Turn off unneeded lights
  - 5-7 days a week
  - 2-4 days a week
  - About once a week
  - Once or twice a month
  - Less than once a month
  - Never or rarely
  - No answer
- During summer, raise your thermostat to 76 degrees or higher
  - 5-7 days a week
  - 2-4 days a week
  - About once a week
  - Once or twice a month
  - Less than once a month
  - Never or rarely
  - No answer
- During winter, lower your thermostat to 68 degrees or cooler
  - 5-7 days a week
  - 2-4 days a week
  - About once a week
  - Once or twice a month
  - Less than once a month
  - Never or rarely
  - No answer
- Unplug appliances when not in use
  - 5-7 days a week
  - 2-4 days a week
  - About once a week
  - Once or twice a month
  - Less than once a month
  - Never or rarely
  - No answer

- Take public transit (bus, train, lightrail, subway, etc.)
    - o 5-7 days a week
    - o 2-4 days a week
    - o About once a week
    - o Once or twice a month
    - o Less than once a month
    - o Never or rarely
    - o No answer

9. Have you done any of the following home energy improvements?
(check all that apply)
- Insulated your attic
- Caulked and weather-stripped your home
- Installed an energy efficient water heater
- Installed an energy efficient furnace
- Installed an energy efficient air conditioner
- Purchased energy efficient refrigerator
- Purchased energy efficient washer or dryer
- Purchased energy efficient small appliances
- Installed energy efficient lighting Installed energy efficient lighting Installed energy
- efficient lighting Installed energy efficient lighting

10. Do you own any of the following?
(check all that apply)
- A motor vehicle that gets over 30 miles per gallon
- A hybrid electric vehicle
- A plug in hybrid electric vehicle (ex: Chevy Volt)
- An all electric vehicle (ex: Nissan Leaf)
- A motorcycle or scooter
- An electric bicycle
- A neighborhood electric vehicle (NEV)

Part C. Opinions & Attitudes

11. How sure are you that global warming (or climate change) is happening?
- Extremely sure global warming is happening
- Very sure global warming is happening
- Somewhat sure global warming is happening
- Not at all sure global warming is happening
- Don't know
- Somewhat sure global warminig is not happening

- Very sure global warming is not happening
- Extremely sure global warming is not happening
- No answer

12. How worried are you about global warming?
    - Extemely worried
    - Very worried
    - Somewhat worried
    - Not very worried
    - Not at all worried
    - No answer

13. Personally, do you think you are well informed about...
    - ...the different causes of global warming
        - o Very well informed
        - o Fairly well informed
        - o Not very well informed
        - o Not at all informed
        - o No answer
    - ...the different consequences of global warming
        - o Very well informed
        - o Fairly well informed
        - o Not very well informed
        - o Not at all informed
        - o No answer
    - ...ways in which we can reduce global warming
        - o Very well informed
        - o Fairly well informed
        - o Not very well informed
        - o Not at all informed
        - o No answer

14. If global warming is happening do you think it is:
    - Caused mostly by human activites
    - Caused mostly by natural causes in the environment
    - Other (please specify)
    - None of the above because global warming isn't happening
    - No answer

15. My actions can make a difference to help reduce global warming
    - Strongly agree
    - Agree
    - Somewhat agree

- Disagree
- Strongly disagree
- No answer

16. The following is a list of reasons why people are interested in joining the CoolCalifornia Challenge.

How important is the following to you?

- Living in a "Cool California City"
    - Very important
    - Important
    - Somewhat important
    - Not very important
    - Not important at all
    - No answer
- Making an environmental statement with your actions
    - Very important
    - Important
    - Somewhat important
    - Not very important
    - Not important at all
    - No answer
- Receiving recognition for your community
    - Very important
    - Important
    - Somewhat important
    - Not very important
    - Not important at all
    - No answer
- Making a political statement
    - Very important
    - Important
    - Somewhat important
    - Not very important
    - Not important at all
    - No answer
- Learning about new technologies
    - Very important
    - Important
    - Somewhat important
    - Not very important
    - Not important at all
    - No answer

- Meeting like-minded people
  - Very important
  - Important
  - Somewhat important
  - Not very important
  - Not important at all
  - No answer
- Getting to know your neighbors
  - Very important
  - Important
  - Somewhat important
  - Not very important
  - Not important at all
  - No answer
- Having fun
  - Very important
  - Important
  - Somewhat important
  - Not very important
  - Not important at all
  - No answer
- Improving where you live
  - Very important
  - Important
  - Somewhat important
  - Not very important
  - Not important at all
  - No answer
- Supporting organizations you care about
  - Very important
  - Important
  - Somewhat important
  - Not very important
  - Not important at all
  - No answer
- Learning how to save money
  - Very important
  - Important
  - Somewhat important
  - Not very important
  - Not important at all
  - No answer
- Receiving discounts for green products
  - Very important

- Important
- Somewhat important
- Not very important
- Not important at all
- No answer

- Winning prizes
  - Very important
  - Important
  - Somewhat important
  - Not very important
  - Not important at all
  - No answer
- Being part of something important
  - Very important
  - Important
  - Somewhat important
  - Not very important
  - Not important at all
  - No answer
- Other (please specify)

17. Taken all together, how would you say things are these days?
Would you say that you are:

- Very happy
- Pretty happy
- Not too happy
- No answer

18. Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?

- People can be trusted
- You can't be too careful in dealing with people
- No answer

19. Please rate how important each value below is as a guiding principle in your life.

- Social status and prestige: recognition for your achievements
  - Extremely important
  - Very important
  - Important
  - Somewhat important
  - Not very important
  - Not at all important
  - No answer

- Power: Control or dominance over people and resources
    - Extremely important
    - Very important
    - Important
    - Somewhat important
    - Not very important
    - Not at all important
    - No answer
- Achievement: Personal success through demonstrating competence according to social standards
    - Extremely important
    - Very important
    - Important
    - Somewhat important
    - Not very important
    - Not at all important
    - No answer
- Hedonism: Pleasure and sensuous gratification for oneself.
    - Extremely important
    - Very important
    - Important
    - Somewhat important
    - Not very important
    - Not at all important
    - No answer
- Self-direction: Independent thought and action—choosing, creating, exploring.
    - Extremely important
    - Very important
    - Important
    - Somewhat important
    - Not very important
    - Not at all important
    - No answer
- Universalism: Understanding, appreciation, tolerance, and protection for the welfare of all people and for nature
    - Extremely important
    - Very important
    - Important
    - Somewhat important
    - Not very important
    - Not at all important
    - No answer
- Benevolence: Preservation and enhancement of the welfare of people with whom one is in frequent personal contact.
    - Extremely important

- Very important
- Important
- Somewhat important
- Not very important
- Not at all important
- No answer

- Tradition: Respect, commitment, and acceptance of the customs and ideas that traditional culture or religion provide.
    - Extremely important
    - Very important
    - Important
    - Somewhat important
    - Not very important
    - Not at all important
    - No answer
- Conformity: Restraint of actions, inclinations, and impulses likely to upset or harm others and violate social expectations or norms.
    - Extremely important
    - Very important
    - Important
    - Somewhat important
    - Not very important
    - Not at all important
    - No answer
- Security: Safety, harmony, and stability of society, of relationships, and of self.
    - Extremely important
    - Very important
    - Important
    - Somewhat important
    - Not very important
    - Not at all important
    - No answer

Appendix A.3. CoolCalifornia Challenge Program Evaluation Survey Questions

17. How would you rate the program website?
- A. Excellent
- B. Good
- C. Fair
- D. Poor
- F. Fail
- No answer

18. What improvements would you recommend for the website?

19. How would you rate the program newsletters?
- A. Excellent
- B. Good
- C. Fair
- D. Poor
- F. Fail
- No answer

20. What improvements would you recommend for the newsletters?

21. How would you rate the communication you have had with local program implementers?
- Excellent
- Good
- Fair
- Poor
- Fail
- No answer

22. What improvements would you recommend for local communication?

23. What energy efficient technologies, if any, did you purchase as a result of this program?

23. What energy conservation or low-carbon practices did you implement as a result of this program?

24. In what ways, if any, has the program changed your attitudes or opinions about climate change or
energy efficiency?

25. Overall, how would you rate the CoolCalifornia Challenge program?
- Excellent

- Good
- Fair
- Poor
- Fail
- No answer

26. What improvements would you recommend for the CoolCalifornia Challenge?
(max length = 5,000 characters)

Appendix A.4. Program manager exit interview questions

Thank you very much for participating in this evaluation research for the CoolCalifornia Challenge pilot project. Your feedback is critically important to help U.C. Berkeley and the California Air Resources Board learn from your experience and to improve similar programs in the future.

This interview should take about 45 minutes but could be shorter or longer depending on the length of the answers you give. Feel free to answer the questions to the extent that you feel comfortable. I will be asking 26 questions, some with multiple parts.

As we mentioned in the consent form, I will be recording audio and later transcribing this interview to accurately capture our conversation. The research team will analyze the interviews and may include quotations or other results in future publications.

During this interview I will be asking about the following: a) the motivations, goals and expectations you had when your city joined the program, and to what extent those goals and expectations were or were not met through the pilot program, b) the target population and any relevant characteristics of participants in your city, c) the resources that were available locally, such as volunteer and staff time, as well as the resources provided by the program, including funding, support, and software; I will ask you to evaluate each of these separately, d) the activities and techniques used by the program, e) the specific project outputs, like newsletters, events, sign ups, energy readings, and raffle prizes, and f) the project outcomes, such as greenhouse gas reductions, awareness and local capacity. At the end of the interview you will also have a chance to tell me anything else you think would be useful for the evaluation of this program.

Do you have any questions? Are you ready to begin? OK, let's get started.

Identification

1. What was your role with the CoolCalifornia Challenge? For example, were you a local program manager or a volunteer?

2. What was your city's placement in the final rankings of the CoolCalifornia Challenge 2013?

A) Motivation, Goals, Expectations

3. Thinking back to when your city first joined the CoolCalifornia Challenge, what were the primary motivations of your city and/or your organizations to join and participate in the program?

4. What specifically did you seek to accomplish by participating in the program and to what extent were those expectations met?

B) Target Population

5. How would you describe Challenge participants in your community to a friend? You can include anything you think that would best characterize this group or groups of individuals.

6. Was this the target population you were originally seeking to engage? If not, how was the population different?

C) Inputs (Resources)

7. Who was primarily responsible for organizing the program at the local level?

8. What resources did the program organizers and/or other organizations in your community contribute? Resources typically include things like volunteer and staff time, funding, print materials, sponsorship, etc.

9. The CoolCalifornia Challenge statewide program sought to provide the following resources to cities: funding, program planning and logistical support, outreach and communications support, and software. I'd like to discuss each of these separately.

    a. Funding:
        i. Your city received (level of funding) in seed money and contributions. How did your organization use this funding?
        ii. Had more funding resources been available, what would have been your primary uses of this funding?
        iii. What would you consider an adequate level of funding to meet your expectations for the program?
    b. Program and logistics
        i. How involved was your city in planning the program?
        ii. Were your concerns heard and addressed?
        iii. Were biweekly calls beneficial? How could these be modified or improved?
        iv. What was your impression of the CBSM workshops? Were they helpful? How could they be improved?
    c. Outreach and communications. How would you evaluate the effectiveness of each of the following?
        i. Newsletters
        ii. E-mail communication with participants
        iii. Print materials
        iv. Interns
    d. Software
        i. The Challenge software was rolled out and changed throughout the one-year pilot project. How would you rate the software?
        ii. What were the aspects of the software that you liked and disliked most?
        iii. How could the software be improved?

iv. What else would you like to tell us about the software?

D) Actions - Activities

10. The Challenge pilot used a number of interventions strategies common with behavior programs, including prompts, persuasive messaging, goal setting, social diffusion, incentives and feedback. Which of these techniques do you find most effective with your target populations? What ideas do you have about improving the use of these strategies?

11. Your city conducted recruitment and outreach events. What did you find to be most effective, and what might you do differently?

12. The program focused primarily on newsletters and direct email communication with participants. How could communication with participants be improved?

13. Our goal with the points system were that it be fair, motivating and easy to understand. Do you think it met these goals? How could we improve the points system? Would simply awarding the winning city based on CO_2 reduced make more sense?

E) Outputs

I'd like to discuss project outputs.

14. How many events did your community hold and what did these events entail?
15. Your city recorded ( ) energy and vehicle readings and () surveys. Are you satisfied with this level of participation?
16. Your city produced ( ) newsletters.
17. How would you evaluate the awards ceremony (ask only if participated)?

F) Outcomes

I'd like to discuss program outcomes.

18. Your city achieved ( ) pounds of greenhouse gas emissions. Are you satisfied with this level of reductions for the pilot?
19. To what extent did the program raise awareness of climate change and mitigation opportunities?
20. How did the city's outputs (events, printed materials, emails, etc.) encourage participation, raise awareness, or demonstrate GHG reductions?
21. To what extent was your community able to raise its own technical and organizational capacity to address community-wide greenhouse gas management through the Challenge?

22. To what extent was social cohesion improved in your community?

G) Other

23. I'd like to ask you a few questions about planning for Round II. What changes would you suggest for a successful program?

24. What would be the ideal timeline for your city?

25. Imagine the Challenge had three grand prizes of $20,000, $10,000 and $5,000 for 1st, 2nd and 3rd places respectively, in addition to $20,000 to distribute to cities based on new participants signed up by December 31. Additional sponsorship money would be distributed based on total points earned in each city at the end of the program. What do you think of this distribution of funds? Would it be better to distribute in some other way?

26. Is there anything else you would like us to know?

Appendix A.5. Note on changes to original program design

The original research contract between U.C. Berkeley and the California Air Resources Board (#10-325) called for a different program design and research hypotheses than outlined in this report. This note briefly explains major changes, why these changes were made, while Appendix H summarizes the extent to which original research hypotheses were tested as a result.

The study was originally designed in contract 10-325 as a yearlong competition between three cities. Cities would be chosen based on their prior experience engaging residents in sustainability. These innovative cities would each receive $12,000 in initial seed money and would lend their experience to help design the program over a six-month long “Phase 0,” and implement programs locally over one year. Additional seed money would be sought from project sponsors. Participants would be required to complete an initial research survey and agree to provide access to their energy data and other reporting requirements agreed to by cities. Participants would also complete an exit survey and a survey 6 months after the end of the competition.

Very early in the contract period ARB and U.C. Berkeley agreed to substantial changes to the program design. Due to concerns that the three chosen cities would not be representative of the California population it was not clear that lessons could be transferred to other communities. At the same time it was understood technologies and practices typically start with innovators and then early adopters (Rogers Everett’s Diffusion of Innovations hypothesis). In order to resolve this conflict the parties agreed to an open statewide competition, allowing any California city the opportunity to compete. This model had the advantages of being more fair, allowing a broader representation of California cities to join (including innovative cities), and the ability to crown the winner the “Coolest California City,” providing additional motivation for cities to join and participate.

The tradeoff of this open competition model was the loss of the ability of U.C. Berkeley to work directly with a small number of cities to develop and test targeted behavior interventions in each city. In part to help ameliorate this tradeoff the new program design included a “Qualifying Round” during which all cities would compete during 3 months, after which only the finalists would continue for the remainder of the program. However, U.C. Berkeley researchers would not be able to work directly with Finalists until almost a full year after the start of the research contract, limiting the ability to design robust interventions for specific populations in each of the three cities.

A second major change to the program design was U.C. Berkeley researchers were not allowed to require participants to take research surveys in order to participate in the program. U.C. Berkeley’s Office of Protection of Human Subjects did not allow this since this would cause harm to those who sought to participate in the program, but were not willing to participate in the the research aspects of the program. As a result, participants were allowed to sign up without taking the research survey, thus limiting the availability of data collected by the research team from all participants.

A third major change was the need to develop sophisticated software to run the statewide competition. In the original design the three participating cities would help with data collection, and only relatively minor changes were envisioned to the existing CoolCalifornia carbon calculator. The new design required a robust and complex software system, including the ability to manually record energy and vehicle odometer readings, uploading photos and stories, communication with participants, raffles, creating and managing teams, calculating points for households, teams and cities and providing program-related content to participants. Only the most basic and essential functionality was ready by the start of the program, while other features were rolled out throughout the yearlong program.

Appendix A.6. Summary of results for research hypotheses

Hypotheses in the original research contract:

a. Program participants will reduce their absolute carbon footprints compared to their baseline assessment.

- Participants used an average of 14% less electricity than the control group, and about the same amount of natural gas.
- Only the electricity and natural gas savings were calculated, not savings from motor vehicles or other aspects of carbon footprints, e.g., food.
- Total greenhouse gas savings from electricity were calculated at 50 metric tons CO_2. Program-wide greenhouse gas savings calculated by the software as "bonus points" were 227 metric tons (~500,000 lbs CO_2).

b. Participants will report being more motivated by social incentives (recognition) and environmental incentives (doing the right thing) than by financial incentives (monetary value of prizes).

- True. Participants did not enroll and participate for the chance to receive a prize (prizes ranked last on a list of 14 motivations). They were primarily motivated to improve where they live, support organizations they care about and help protect the environment.
- However, there appears some discrepancy between what participants report and what is observed (e.g., more vigorous participation during intense competition).

c. Lower-income households will exhibit more financial motivations to participate.

- True, although the effect was not large.
- Conservatives and less educated participants also expressed somewhat higher financial motivations.

d. Participants in EcoTeams will reduce more than participants not in EcoTeams.

- EcoTeams were not sufficiently studied because the teams feature of the software was added too late in the program.

e. Program participants with prior relationships and greater expectation of future interactions with other program participants will reduce more than participants without strong pre-existing social connections.

- EcoTeams were not sufficiently studied because the teams feature of the software was added too late in the program.

f. Those with more altruistic environmental motivations for participating will have lower starting carbon footprints than participants with primarily social and financial motivations for participating.

- This was not studied due to the difficulty of tabulating the results for each of the roughly 10,000 individual electricity, natural gas and motor vehicle reports.

g. Program participants with higher starting carbon footprints will reduce more than households with lower carbon footprints.

- This was not studied due to the difficulty of tabulating the results for each of the roughly 10,000 individual electricity, natural gas and motor vehicle reports.

h. Households and communities with higher carbon footprints will reduce more, in absolute terms and as a percentage, than households with lower carbon footprints due to the prevalence of “low-hanging-fruit” actions and comparison with peers.

- This was not studied due to the difficulty of tabulating the results for each of the roughly 10,000 individual electricity, natural gas and motor vehicle reports.

i. Communities will achieve roughly similar results overall.

- False. Non-finalist cities (except San Jose, which used a separate proprietary software platform and can not be directly compared), did not achieve nearly as many points as finalist cities.

j. Savings will persist over time

- Since we did not have access to energy data for participants after the program we could not evaluate persistence. The follow up survey 6 months following the end of the program provided insufficient evidence for persistence of behaviors.

Additional hypotheses tested:

k. The program will appeal almost exclusively to liberal environmentalists.

- False. While most participants tended to be fairly well informed about the causes and consequences of climate change (per self-reported responses), and also were more likely to be politically liberal and highly educated (both strong determinants of pro-environmental beliefs and actions) over 30% of participants were politically conservative or neutral and earned nearly as many points per household as liberals.

l. The program will appeal mostly to young people who tend to be more interested in online games.

- False. Only 15% of participants were under 35 and young persons earned fewer points per household than older participants.

m. Households with children will earn more points than households without children since they will be more interested in the health and well-being of their children and future generations.

- False. Households without children earned more points on average than households with children. This is possibly due to the larger number of seniors in the program and lack of messaging on health benefits (as in the Delmas et al, 2013 study).

n. Participants will primarily be interested in receiving recognition for their city and prizes for themselves (both extrinsic motivations).

- False. Earning recognition for cities ranked 11 out of 14 motivations and earning prizes ranked last. Participants were primarily interested in improving where they live, supporting organizations they care about and making an environmental statement

o. Participants will have primarily universalistic values (defined as understanding, appreciation, tolerance, and protection for the welfare of all people and for nature).

- False. While universalism was the highest rated value overall, self-direction, security and benevolence were also strong values.

p. Manually entering energy data will be a major barrier preventing broad participation in the program.

- False. Over 900 households successfully manually entered over 10,000 individual electricity, natural gas, odometer readings and "kudo points" reports.

q. Households for which energy data are automatically received by software will reduce more energy since they will be able to focus on reductions rather than entering data as the primary means of participation.

- This appears to be false. The city of San Jose was the only city to have data automatically imported into a software platform (in this case the Wattzon platform), but San Jose participants earned only 1,139 Bonus Points per active household compared to an average of 1,568 Bonus Points per active household, on average, and over 2,200 Bonus Points per active households in Davis and Chula Vista. Bonus Points are calculated as CO_2 savings compared to the household's previous consumption, adjusting for weather. Active households are defined as households with more than one month of energy data. This is not a truly fair comparison since the Wattzon platform used by San Jose did not include motor vehicles; however, San Jose participants had data for all 13 months for all active households, while other Challenge participants only had data for those months in which they reported data (an average of 5 months per active household). The Wattzon software platform used by San Jose participants was also fundamentally different than the Challenge software in many ways so comparisons are not really appropriate (and are therefore not addressed in the study).

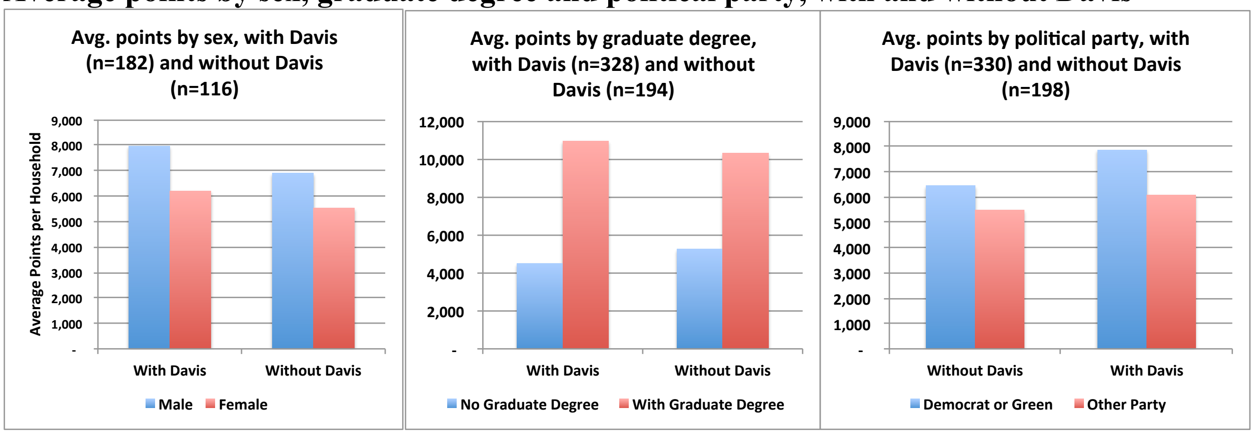
- It may be that manually entering data each month is a prompt to reduce energy and a way to demonstrate active engagement with the program.
- Future programs should experimentally test manual data entry and automated data entry in order to test the efficacy of both approaches.

Appendix A.7. Analysis of results with and without Davis

The winning city, Davis, is a university town with a highly educated population. As shown in Figure 8, over 50% of Challenge participants from Davis filling out the survey have a graduate degree. It is reasonable to ask whether removing Davis participants from the analysis would affect all of the study results, and not just the energy savings. This section briefly explores removing Davis participants from the analysis of survey results and the impact this has on results.

As shown in Figure 33, excluding Davis from the results does not affect the results for key survey results, including average points by graduate degree, sex or political party.

Average points by sex, graduate degree and political party, with and without Davis



Appendix A.8. Project budget overview

The budget below contains all expenses for the design, implementation and evaluation of the CoolCalifornia City Challenge pilot project 2012-2103, not including in-kind contributions from cities and volunteers.

2012-2013 TOTAL PROJECT BUDGET	**$**	**432,504**
California Air Resources Board	**$**	**300,004**
1 Labor & Employee Fringe Benefits	$	226,223
2 Seed and prize money to cities	$	36,000
3 Travel & Subsistence	$	4,520
4 Photocopying & Printing	$	2,875
5 Mail, Telephone, and Fax	$	4,371
6 Materials & Supplies	$	1,250
7 Awards	$	1,000
8 Indirect Cost	$	23,765
Renewable and Appropriate Energy Laboratory	**$**	**100,000**
1 Software designer and manager	$	65,000
2 Student programmers	$	35,000
Next Ten	**$**	**5,000**
1 External software developer	$	5,000
Pacific Gas & Electric	**$**	**27,500**
1 Seed money to cities ($2,500 x 7 cities)	$	17,500
2 Program support (software)	$	10,000
Breakdown by task	**$**	**432,504**
1 Program design, implementation and evaluation	$	240,239
2 Funding to cities	$	53,500
3 Software	$	115,000
4 Indirect cost	$	23,765

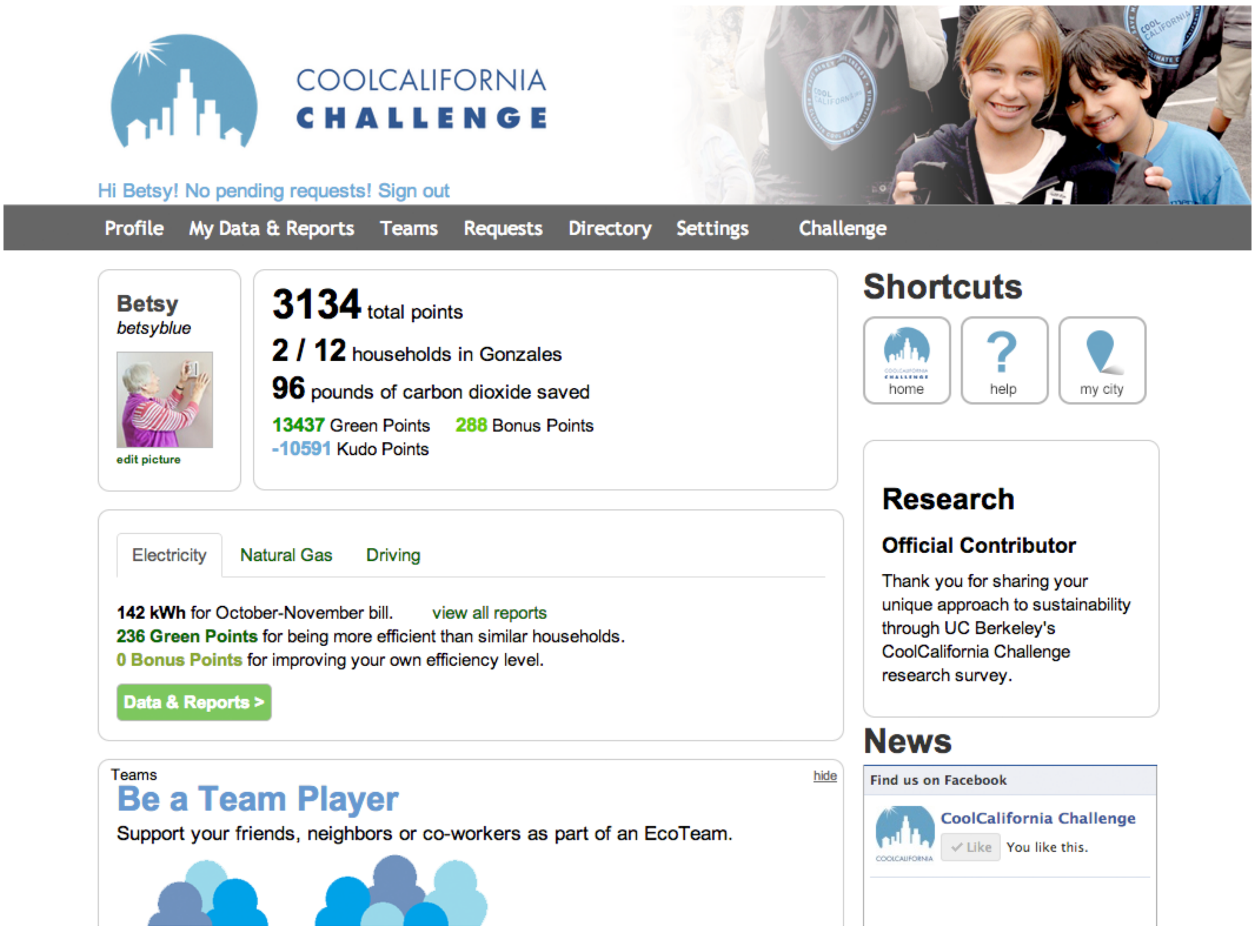
Budget for 2014 Competition

At the time of this writing, Round 2 of the CoolCalifornia City Challenge is now complete. The program achieved 40% higher participation (3,775 households) and preliminary calculations indicate that Round 2 achieved 60% more CO_2 savings as calculated by Bonus Points (360 metric tons CO_2 compared to 225) in half the time (six months) and less than half the budget. The program also engaged ten very diverse cities, lending evidence that the program model is highly scalable to cities across California.

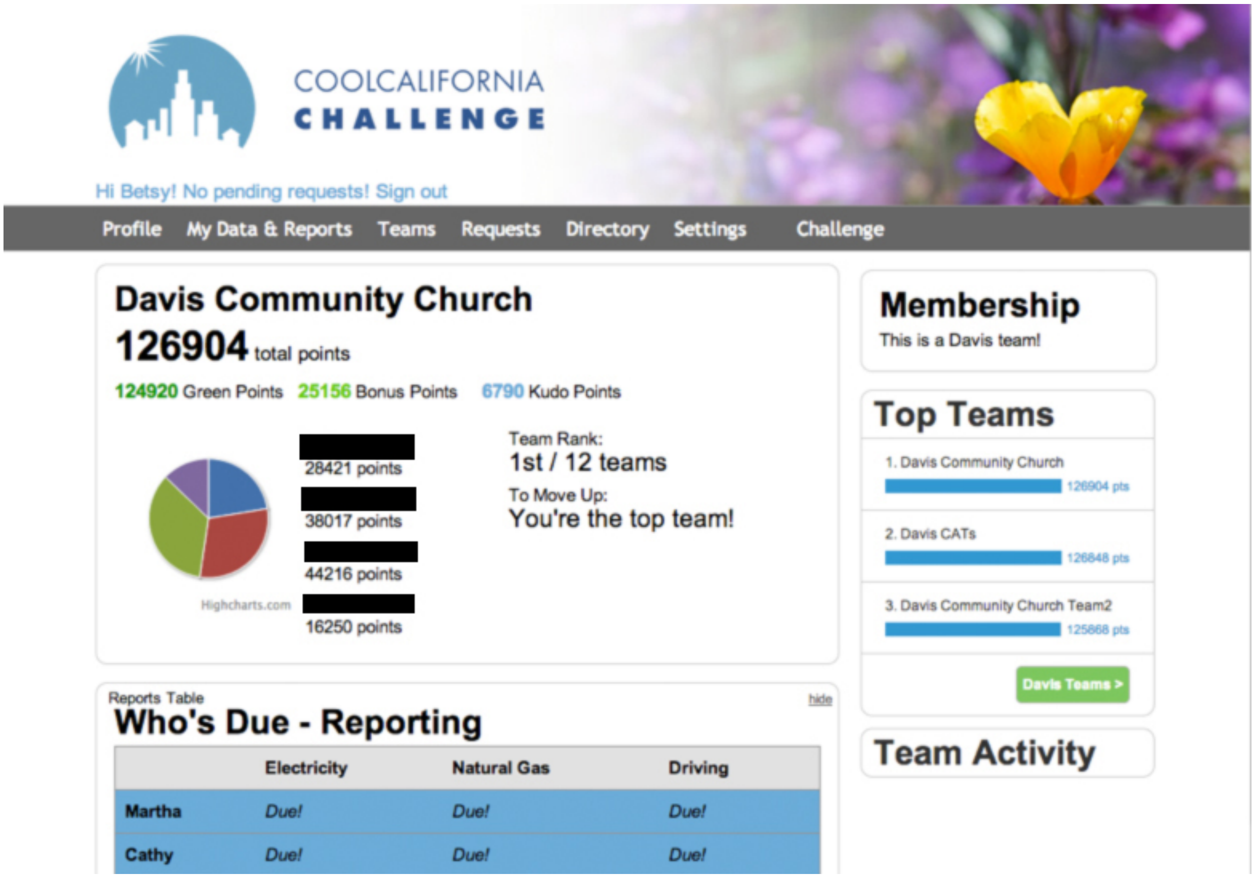
The total project budget for the CoolCalifornia City Challenge in 2014 was $150,000, including $100,000 in seed and prize money to cities from Energy Upgrade California and $50,000 in project management and software development for U.C. Berkeley (funding also from Energy Upgrade California). This does not include in-kind contributions from the participating cities and the California Air Resources Board.

Appendix A.9. Screenshots of CoolCalifornia Challenge website

a. Screenshot of sample user profile page



b. Screenshot of sample team page

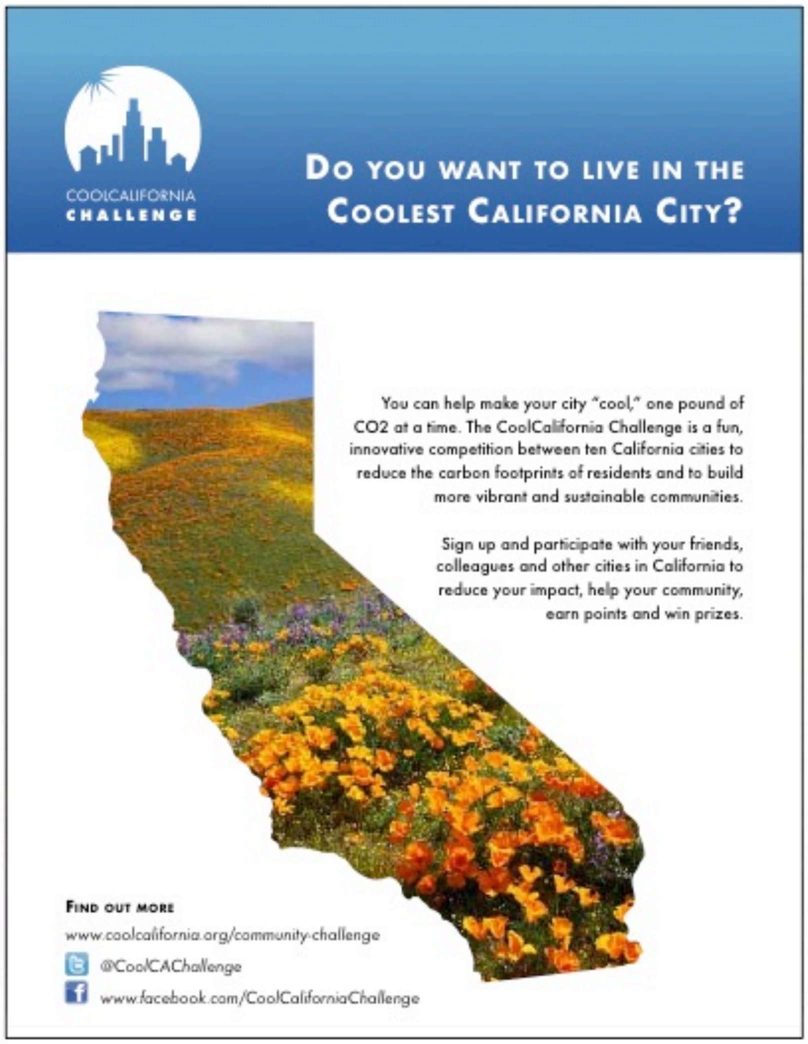


c. Screenshot of final scoreboard

Appendix A.10. Example program materials

City Flyer/Letterhead - *Sacramento*

Outreach Flyer



You can help make your city cool, one pound of CO_2 at a time. The CoolCalifornia Challenge is a fun, innovative competition between ten California cities to reduce their community-wide carbon footprints and build more vibrant and sustainable communities. Sign up and participate with your friends,colleagues and other cities in California to reduce your impact, help your community, earn points and win prizes.

COOLCALIFORNIA
CHALLENGE

Join Today!

www.coolcalifornia.org/community-challenge

www.facebook.com/CoolCaliforniaChallenge

@CoolCAChallenge

Ahora puedes ayudar a tu ciudad a ser "cool", una libra de CO_2 menos cada vez. El Desafío CoolCalifornia es una competición divertida e innovadora entre 10 ciudades de California para reducir la huella de carbono de sus residentes y para construir comunidades más dinámicas y sostenibles. Regístrate y participa con tus amigos, colegas y con otras ciudades de California para reducir tu impacto ambiental, ayudar a tu comunidad y ganar puntos y premios.

COOLCALIFORNIA
CHALLENGE

¿Quieres saber más?

www.coolcalifornia.org/community-challenge

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Davis, CA

2013

COOLEST

CALIFORNIA CITY

The CoolCalifornia Challenge • 1st Place

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2013

COOL

CALIFORNIA CITY

The CoolCalifornia Challenge • 2nd Place

Tracy, CA

2013

COOL

CALIFORNIA CITY

The CoolCalifornia Challenge • 3rd Place