EnergyChoice Final Report

Developing a Toolkit to Optimize Community Choice Energy Programs

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The Group Project is required of all students in the Master of Environmental Science and Management (MESM) Program. The project is a year-long activity in which small groups of students conduct focused, interdisciplinary research on the scientific, management, and policy dimensions of a specific environmental issue. This Group Project Final Report is authored by MESM students and has been reviewed and approved by:

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Table 1. Summary of Acronyms

Acronym	**Full Name**
AB	Assembly Bill
AHP	Analytic hierarchy process
BEV	Battery electric vehicle
CAISO	California Independent System Operator
CCE	Community Choice Energy
CEC	California Energy Commission
CO_2e	Carbon dioxide equivalent
CPUC	California Public Utilities Commission
DALY	Disability adjusted life years
EV	Electric vehicle
GHG	Greenhouse gas
GWP	Global warming potential
HVAC	Heating, ventilation, and air conditioning
ICEV	Internal combustion engine vehicle
IOU	Investor owned utility
JPA	Joint powers authority
LCOE	Levelized cost of electricity
$MTCO_2e$	Metric ton of carbon dioxide equivalent
MW	Megawatt
MWh	Megawatt hour
NEM	Net energy metering
NOx	Oxides of nitrogen
PG&E	Pacific Gas & Electric
PHEV	Plug-in hybrid electric vehicle
PM10	Particulate matter with diameter ≤10 microns
PM2.5	Particulate matter with diameter ≤2.5 microns
RPS	Renewable Portfolio Standard
SCAQMD	South Coast Air Quality Management District
SCE	Southern California Edison
SDG&E	San Diego Gas & Electric
SOx	Oxides of sulfur
TCM	Technology choice model
VOC	Volatile organic compound
ZNE	Zero net energy

Abstract

California's Renewables Portfolio Standard requires 50% of its retail electricity sales to come from renewable sources by 2030. A growing number of local governments have taken steps to meet and exceed these standards by forming Community Choice Energy (CCE) agencies that supply higher renewable content electricity to their constituent cities and counties at lower rates than the investor-owned utilities. CCE agencies also provide co-benefits via community-serving energy programs, but lack adequate tools to evaluate and optimally design potential programs. This project provides tools and knowledge to help CCE agencies provide greater net benefits to their communities. We built an interactive toolkit that helps agencies evaluate potential electric vehicle rebate and residential solar photovoltaic financing programs based on economic costs and benefits, greenhouse gas emission reductions, and health impacts. The toolkit is built upon a technology choice model framework that incorporates purchase costs, operating costs, and variability in consumer preferences to predict program outcomes. We also compiled a guide containing successful practices for implementing effective energy programs based on interviews with industry experts, case studies, and literature review. The toolkit and successful practices guide will help CCE agencies identify measurable effects of their programs and inform their decisions when developing new programs.

Executive Summary

California can increase its renewable energy portfolio at the local level by allowing communities within the state to engage in alternative energy supply contracts from those of investor owned utilities (IOUs). Community Choice Energy (CCE) agencies are not-for-profit local government programs that supply electricity to their constituent cities and counties. Through their energy procurement decisions, rate-based programs, and other programs, CCE agencies can support renewable energy adoption and provide additional co-benefits to their communities, such as improving public health, fostering environmental justice and energy democracy, alleviating stress on the electric grid, and providing opportunities in local resource development, asset ownership, and energy efficiency.

Although CCE has the potential to serve as a test bed and accelerator for clean energy innovation, CCE agencies lack adequate tools to evaluate the cost-effectiveness of their programs. This makes it challenging for agencies to implement programs in ways that will be most beneficial to their communities. This project provides CCE agencies with tools and knowledge that they can use to provide greater net benefits to their communities.

We built a toolkit with which agencies can evaluate potential energy programs based on three main metrics: economic costs and benefits, greenhouse gas reductions, and health impacts. We developed models from available data on CCE agency programs, other relevant energy programs and publicly available data, and correspondence with agency staff. Models were incorporated into a toolkit that quantifies the costs and benefits of certain CCE agency programs according to the chosen metrics. The toolkit includes models to assess programs that offer EV incentives, residential solar financing, and indoor fuel switching incentives.

In addition, we compiled a successful practices guide for CCE agencies. We compiled successful practices and recommendations for developing effective energy programs through literature review, interviews with CCE agency staff, and interviews with employees from similar clean energy organizations. The toolkit and successful practices guide are expected to help CCE agencies identify measurable effects of their programs and inform their decisions when creating new programs.

Project Objective

The project's objective is to provide tools and knowledge to help Community Choice Energy (CCE) agencies select and design programs that will maximize net benefits to their communities. Our interactive assessment tool and documentation of successful practices will inform agencies of existing program designs and help them learn which ones will best provide a range of benefits. The main benefits to be assessed fall into the categories of monetary costs and benefits, greenhouse gas (GHG) emission reductions, and public health. This project will be useful to emerging and operational CCE agencies, as well as communities considering CCE.

Project Significance

CCE agencies have the potential to reduce GHG emissions and mitigate climate change by accelerating the transition from fossil energy to renewable energy sources, through their energy procurement, programs, and other activities. CCE can foster environmental justice and energy democracy by transferring decision-making about energy sources, rates, local energy projects, employment, and other matters from distant, private utility boardrooms to public local government meetings. Agencies can produce electricity within their jurisdictions and hire local workers to further increase benefits to their communities. The agencies can also alleviate stress on the electric grid by forming mini- or micro-grids and supporting small-scale power plants.

One method for agencies to deliver benefits to their communities is by using net revenues from their energy sales to develop and implement clean energy programs. These programs can take many forms, and agencies currently lack the tools to estimate demand for the programs and to evaluate the potential benefits and costs of offering such programs. This project will provide CCE agencies with information and tools to establish effective clean energy programs and evaluate their benefits. This will help agencies maximize the effectiveness of their programs for the benefit of their communities.

The client for this project is the Center for Climate Protection. Our project's broader audience includes CCE agency staff, city and county elected officials and staff, and consultants. Additional beneficiaries might include state-level policymakers, load serving entities, energy analysts and project developers, clean energy and social justice advocates, and stakeholders in other states with CCE laws.

Overview of CCE Agencies

California authorized the creation of CCE agencies with the enactment of AB 117 in 2002, giving local governments a new way to procure electricity (Assembly Bill, 2002). CCE agencies can be created in communities served by one of California's investor-owned utilities (IOUs): PG&E, SCE, or SDG&E. Under AB 117, CCE agencies are the default energy providers in their service areas; residents automatically receive agency-provided electricity unless they choose to remain with their IOU. While CCE agencies procure their own energy, the IOUs are still responsible for transmitting the energy to residents (Ferguson, 2016). This creates a hybrid energy structure requiring close cooperation between CCE agencies and IOUs to ensure that communities have reliable power supplies (Xia, 2017).

The first CCE agency in California launched in 2010. As of May 2017, eight CCE agencies are operational throughout California, serving approximately 810,000 customers, and several other areas are considering CCE (Table 2).

The most common goals of the early CCE agencies are having competitive rates, reducing GHG emissions, reaping local economic and workforce benefits, increasing renewable energy usage, adding local renewable energy projects, maintaining stable or reliable rates, and gaining local control. Additional goals cited include customer choice, benefits to the community, energy efficiency, energy independence, and environmental justice. The agencies must reach and maintain financial stability to reach these goals, but beyond that they prioritize these goals over profitability, as not-for-profit government agencies. The agencies can progress toward these goals because they aggregate the purchasing power of their residents, businesses, and municipalities.

CCE agencies have demonstrated a variety of strategies to work toward their goals. They generally offer higher renewable energy content electricity at lower rates compared to IOUs. All California CCE agencies to date set rates once per year, helping customers to anticipate their energy costs compared to IOUS, which set new rates more frequently. Some also have goals or have already accomplished projects to increase local energy generation and local building jobs. Most agencies already offer net metering, feed in tariffs and a 100% renewable energy option. Finally, net revenues generated by the agency can be put toward local energy programs, and several CCE agencies also promote state-run energy efficiency incentives and projects. Local energy programs of interest so far include local distributed energy resources development, free energy efficiency audits, electric vehicle (EV) incentives, and energy storage programs.

Besides working toward their mission-related goals, CCE agencies implement local programs to demonstrate their value to their customers. The programs, as well as their ability to charge lower rates than IOUs, can help CCE agencies retain customers. Residents and commercial customers may opt out and return to IOU service at any time. If the opt-out rate is high enough, an agency risks having to sell off previously contracted power at a loss, or even losing the customer base and public mandate to appear viable (Sonoma County Water Agency, 2011).

Table 2. Summary of Operating CCE Agencies in California as of May 2018

Name	Area Served	Launch Date	Accounts
Apple Valley Choice Energy	Town of Apple Valley	April 2017	27,000
Clean Power Alliance	Unincorporated Los Angeles County, Unincorporated Ventura County and the cities of: Agoura Hills, Alhambra, Arcadia, Beverly Hills, Calabasas, Camarillo, Claremont, Carson, Culver City, Downey, Hawaiian Gardens, Hawthorne, Malibu, Manhattan Beach, Moorpark, Ojai, Oxnard, Paramount, Redondo Beach, Rolling Hills Estates, Santa Monica, Sierra Madre, Simi Valley, South Pasadena, Temple City, Thousand Oaks, Ventura, West Hollywood, and Whittier.	February 2018	1,000,000
Clean Power SF	City and County of San Francisco	May 2016	78,000
Lancaster Choice Energy	City of Lancaster	May 2015	50,000
MCE Clean Energy	Marin and Napa Counties, unincorporated Contra Costa County, and the cities of Benicia, Concord, Danville, El Cerrito, Lafayette, Martinez, Moraga, Oakley, Pinole, Pittsburg, Richmond, San Pablo, San Ramon, and Walnut Creek	May 2010	250,000
Monterey Bay Community Power	Monterey, San Benito and Santa Cruz Counties	March 2018	270,000
Peninsula Clean Energy	San Mateo County	February 2016	210,000
Pico Rivera Innovative Municipal Energy	City of Pico Rivera	September 2017	16,000
Pioneer Community Energy	Placer County, and cities of Auburn, Colfax, Lincoln, Rocklin and the town of Loomis	February 2018	80,000
Redwood Coast Energy Authority	Humboldt County	May 2017	66,000
Silicon Valley Clean Energy	Unincorporated Santa Clara County	April 2017	235,000
Sonoma Clean Power	Sonoma & Mendocino Counties	May 2014	195,000

Toolkit Overview

Selected Programs

We selected three programs to model in our toolkit:

- Electric vehicle (EV) incentives,
- Residential solar financing, and
- Indoor fuel switching incentives.

These were chosen based on correspondence with CCE agency staff and the Center for Climate Protection to determine which programs were being considered by agencies and which would be most useful to include in the toolkit. We developed the EV incentives and solar financing models using a technology choice model (TCM) framework, described below. These models allow a CCE agency user to input specifications of their planned programs. The models then predict uptake of each program by residents, and associated GHG emission reductions and health impacts. We developed a simpler fuel switching model that calculates the GHG and health impacts associated with switching a given number of conventional home heating systems with air source heat pumps.

Technology Choice Model

TCM is an economic input output model that predicts consumer choices given a number of purchasing options with distinct costs (Kätelhön et al., 2016). The model assumes that consumers always choose the lowest cost option from a set of comparable purchases, but that subjectivity, imperfect access to information, and other stochastic factors add uncertainty to purchasing behavior. Thus, the model assigns uncertainty to each cost category associated with a purchase option, and varies costs based on these uncertainties using Monte Carlo simulations to reflect the various preferences of individual consumers.

Monte Carlo simulations use given probability distributions to vary the costs of each purchase option over thousands of iterations. This simulates the range of total costs after accounting for stochastic factors. The likelihood of a certain purchase option being the least cost option across simulations represents its final market demand.

Probability distributions for cost categories can be altered to match model predictions with empirical data. Once calibrated, the TCM can predict changes to market demand in response to changes to the total cost of one or more purchase options.

Environmental and Health Impacts

Background and Overview

The goal of this toolkit is to help CCE agencies calculate monetary, environmental, and health benefits of the selected clean energy programs. This section of the report provides an overview of the environmental and health impacts of criteria pollutant and GHG emissions, and then explains the methods we used to calculate the benefits of pollutant and emissions reductions associated with each clean energy program.

Criteria Pollutants and Human Health

Combusting fossil fuels for transportation and energy generation emits criteria air pollutants. The Clean Air Act currently regulates six criteria air pollutants: ground-level ozone, carbon monoxide, NOx, SOx, particulate matter, and lead. Particulate matter is further classified into PM10 and PM2.5 based on the particle's diameter. Ozone is not emitted directly but formed when NOx and volatile organic compounds (VOCs) react in sunlight (USEPA, 2017). VOCs are not a federally regulated criteria pollutant, but may be regulated at local and state levels.

Exposure to criteria air pollutants significantly affects human health (USEPA, 2011). In 2013, 5.5 million people died prematurely from air pollution, costing the world $225 billion in lost labor income and $5 trillion in welfare losses (World Bank, 2016). Of the criteria pollutants, PM2.5 and ozone are associated with the highest rates of premature deaths, driven primarily by on-road transportation and energy generation (Caiazzo et al., 2013, Laden et al., 2006). P.M 2.5 is especially dangerous because it can penetrate deep into human lungs and may consist of toxic substances (USEPA, 2011). SOx emissions harm both human health and ecological functions, including by causing respiratory illness, cardiovascular disease, impaired visibility, acidified water bodies, and damaged crops (Srivastava et al., 2001). Over 85% of the benefits of air pollution, control programs stem from reducing premature mortality and morbidity, with the remaining benefits coming from improved visibility and ecological resources (USEPA, 2011).

Combustion criteria pollutants can be managed before or after combustion, but current control technologies do not concurrently control GHG emissions. For example, technologies like catalytic converters and scrubbers are highly effective at removing specific criteria pollutants after combustion, but do not reduce GHG emissions (Heck and Farrauto, 2001; Srivastava et al., 2001; Miller, 2006). CCE agencies' missions extend beyond air pollution to include GHG emissions reduction, so agencies are not expected to invest in criteria pollutant controls, though these have proven highly cost effective in terms of societal benefits (USEPA, 2011). Rather, agencies will likely look to programs that reduce air pollution as a co-benefit of reducing GHG emissions. Additional criteria pollutant control requirements will come from either the federal government, state government, or local air districts.

Greenhouse Gas Emissions

Greenhouse gases are emitted alongside criteria pollutants during fossil fuel combustion, so reducing GHG emissions helps reduce criteria pollutant emissions. Recent studies show 150 million premature deaths can be avoided by reducing GHG emissions to keep warming under 2° C due to co benefits of reducing air pollutants (Shindell et al., 2018). GHGs do not directly affect human health like criteria pollutants but GHGs can cause indirect health impacts. For example, under a business as usual scenario, age adjusted mortality rates could increase up to 3% because of higher frequencies high temperature days (Deschênes and Greenstone, 2011). Indirect human health impacts from GHG emissions are diffuse and difficult to quantify; therefore, in this project we do not consider indirect human health impacts from GHG emissions.

In California, 19% of GHG emissions are from electricity generation and 37% are from transportation (CARB, 2017). There are few technological options to reduce GHG emissions post-combustion. There are some pilot carbon capture and sequestration projects in place but the technology is not ready to be scaled up (Global CCS Institute, n.d.). Reducing energy demand and switching away from carbon-based fuels are the most effective ways to reduce carbon emissions, and the most relevant methods that CCE agencies can use. We evaluate three potential programs to reduce GHG emissions: incentivizing EVs, financing rooftop solar PV and switching away from natural gas based heating systems. Each of these programs involve using electricity instead of fossil fuels to supply energy services. CCE agencies have high renewable contents in their electricity, minimizing the GHG emissions from increasing electricity consumption when people switch to EVs or electric based heating systems.

The Rebound Effect

The rebound effect must be considered when predicting the criteria pollutant and GHG emissions of any energy programs. The rebound effect is an increase in the use of an energy service if that service can be produced more efficiently. For example, Norwegian households with heat pumps do not have lower energy bills because they choose to use their savings towards increasing the indoor room temperature (Halvorsen and Larsen, 2013). This is an extreme example where the rebound effect fully negates energy efficiency benefits. Similarly, EV drivers drive 3% more than conventional vehicle drivers, which may decrease expected GHG emission reductions (Sun et al., 2017).

Methods

GHG and criteria pollutant emissions are the primary environmental impacts calculated. In the EV model, we calculated the emissions avoided by keeping new internal combustion engine vehicles (ICEVs) off the road and the emissions generated from the electricity to charge the EVs and plug-in hybrid electric vehicles (PHEVs). Similarly, in the heat pump model we calculated the emissions avoided by switching away from a natural gas furnace and the emissions generated from the electricity used to power the heat pump. The net change is the environmental benefit of the EV incentive and heat pump programs. In the solar PV model, we calculate the emissions avoided by generating energy from PV instead of the agency mix.

In all models, once the total quantity of emissions is calculated we determine the value of these avoided emissions. The default value of avoided GHG emissions (CO_2e) is $13 per ton, based on the approximate market price of CO_2e in California's cap and trade market in 2017. Agencies can adjust the value of carbon used in the model if they have their own internal carbon value.

The value of criteria pollutants are based on review of the literature. Several studies have attempted to quantify the external costs of air pollution from electricity generation and transportation. The majority of the damages come from increasing premature mortality (USEPA, 2011). The health impact from a unit of pollution depends on how the pollutant is dispersed and the population density near the source. As a result, studies have shown a wide range of potential damages and studies examine a variety of impacts. Some studies just look at health impacts (Fann et al., 2009) while other include environmental and visibility improvements (National Research Council, 2010; Holland et al., 2005). We adjusted each study's results by scaling the value of a statistical life (VSL) in the study to the current EPA VSL and then inflated to 2016 dollars. For European studies, we converted Euros to USD using the exchange rate during the year on which the results are based. Given that the vast majority of the value in any of the studies is based on changes in premature mortality, we believe scaling the entire value by the difference in VSLs is a reasonable approximation.

The models present average, low, and high health impact values. We understand that using an average value for a unit of pollution is an oversimplification and may not be representative of the impact in a particular area. Given the range of potential values we suggest that more rural areas use the lower values while more urban area use the higher values due to the number of people that may potentially be affected. It should be noted that CCE agency's missions are to create more sustainable societies by increasing energy efficiency and renewable energy procurement. Reducing air pollution is not listed as a primary goal, but becomes an added benefit to their communities.

Electricity Emission Factors

Emissions from electricity production are calculated according to the following equations. EPA's guidance on GHG emission factors provides emissions per MMBTU (USEPA, 2016). We multiply this by the heat rate (MMBTU/kWh) for each thermal energy source to develop electricity generation GHG emission factors. GHG emissions from large hydroelectric plants are referenced from the Center for Climate and Energy Solutions.

$$EF_{elec-fuel} = (EF_{heat-fuel})(HR)$$

And

$$EF_{elec-mix} = (EF_{elec-fuel})(P)$$

where,

$EF_{elec-fuel} = emission\ factor\ from\ electricity\ generation\ from\ fuel\ source\ (\frac{kg}{kWh})$

$EF_{heat-fuel} = emission\ factor\ for\ thermal\ source\ (\frac{kg}{MMBTU})$

$HR = heat\ rate\ (\frac{MMBTU}{kWh})$

$EF_{elec-mix} =$
$emission\ factor\ from\ electricity\ generation\ from\ fuel\ source\ in\ agency\ mix\ (kg/kWh$

$P = proportion\ of\ fuel\ source\ in\ agency\ mix$

All GHG emissions are in carbon dioxide equivalent (CO_2e). Methane (CH_4) and nitrous oxide (N_2O) emissions are multiplied by their respective global warming potentials (GWP) as shown in Appendix A. Electricity emission factors are summarized in Appendix B.

Emissions of criteria pollutants are estimated using USEPA AP-42 emission factors. Natural gas can produce electricity in multiple ways, so we average the boiler and turbine emission factors for our calculations. We assume that large hydroelectric plants emit no criteria pollutants, and that small hydroelectric, wind, and solar electricity sources emit no GHGs or criteria pollutants. Electricity mixes are determined from power content labels. If a power content label indicates "unspecified sources," we assume this portion is sourced from natural gas. These emission factors are national averages and may not represent the actual emission factors of a given power plant.

Electric Vehicle Incentives Program

Background and Literature Review

One of the programs currently being considered or implemented by multiple CCE agencies is the provision of incentives for EV purchases. Replacing ICEVs with EVs can reduce fossil fuel consumption in the transportation sector, which accounts for 37 percent of California's total GHG emissions (CARB, 2017). This reduction is greater for CCE than for IOU customers, because CCE-procured electricity tends to have a higher renewable energy content than does IOU-procured electricity. Increasing EV use also helps fulfill parts of CCE agency goals to reduce local pollution. In this section we review existing literature on hybrid and EV incentives, including a discussion of the Drive EverGreen program, a pilot EV incentives program run by Sonoma Clean Power (SCP), the CCE agency operating in Sonoma County.

Effectiveness of Incentive Programs

Assessments of hybrid-electric and EV incentives have had mixed results, though most show that incentives can play a significant role in driving vehicle purchases. Chandra et al. (2010) estimated that 26% of hybrid vehicle sales in Canada could be attributed to the availability of $1,000 hybrid subsidies. Diamond (2009) found that the effect of incentives in the US varied by state, with some state incentives showing little or no effect on hybrid vehicle sales. Incentives that immediately benefited customers, such as excise and sales tax waivers, were more effective than ones that delayed benefits, like tax credits and registration fee waivers.

Sierzchula et al. (2014) sought to evaluate the impact of subsidies across national EV markets. They isolated the effect of incentives on EV market share across 30 national EV markets and found a $1,000 increase in incentive leads to a 0.06% increase in market share. They also found that increasing charging infrastructure significantly increased EV market share.

Survey data from California's Clean Vehicle Rebate Program suggest availability of rebates is an important factor in the decision to buy EVs (Center for Sustainable Energy, 2017c). Nearly half (46%) of survey respondents rated CVRP rebate extremely important to being able to purchase a PHEV or Battery Electric Vehicle (BEV). An additional 28% ranked it very important. Similarly, 45% rated federal incentives extremely important, and 26% very important. Incentive amounts varied widely, but survey responses were not matched with the incentive that customers received, so we are unable to conclude from this data what importance rating is given to a specific amount of incentive.

Estimates of the cost-effectiveness of GHG emission reductions from hybrid and EVs vary significantly. Chandra et al. (2010) found cost-effectiveness of hybrid GHG emission reductions to be between $129 and $270 per ton of CO_2e reduced, depending on the vehicles being replaced by the hybrids. Plotkin and Singh (2009) estimated cost-effectiveness of a $7,500 subsidy at $400-600 per ton CO_2e reduced, depending on the type of vehicle to which the subsidy is applied. Kammen et al. (2008) estimated cost-effectiveness of using PHEVs to reduce GHG emissions by assuming an incentive amount equal to the cost difference between vehicles after considering fuel savings. They find a range in cost-effectiveness of $163-2,498, depending on vehicle type and source electricity mix. Agencies with higher percentages of GHG free electricity will have more cost-effective incentive programs. The base price of EVs decreases as the cost of the battery pack decreases; given current battery pack cost trends, therefore, agencies will need to offer smaller incentives to achieve the same amount of uptake in the future (Nykvist & Nilsson, 2015).

Sonoma Clean Power Pilot Program

Sonoma Clean Power launched a pilot EV rebate program for SCP customers from October 2016 through January 2017 (Center for Sustainable Energy, 2017a). Customers redeemed 206 rebates over the course of the program, primarily for leased vehicles. The pilot program used a voucher system under which 522 applicants were approved. Of these, 108 were low-income customers eligible for a $5,000 rebate. All other applicants were eligible for $2,500 rebates on leased or purchased EVs. Two EVs were eligible for rebates: The Nissan LEAF and BMW i3. The Nissan LEAF was much more popular, with only 28 incentives used for the BMW i3. SCP also worked with dealers to offer additional discounts to SCP customers, which supplemented those offered by SCP.

Sonoma Clean Power used the AFLEET tool to estimate emissions reductions from their pilot program. The tool compares the lifetime environmental and economic costs and benefits of two sets of vehicle fleets input by the user. To construct their counterfactual vehicle fleet, SCP surveyed program participants to determine the type of car each customer would drive had they not received a rebate. Eighty-eight percent reported that they would not have adopted an EV otherwise. SCP estimates emissions reductions of 1.8 tons CO_2e per $100 spent on incentives, or $56 per ton CO_2e reduced. This value does not account for program administration costs, however, or the additional rebates that Sonoma County negotiated with EV dealers.

Methods

Model Overview

We constructed our model using the TCM framework to predict the direct impact of an incentive on EV sales. The model predicts the market share of 30 vehicle segments based on their total costs, including a price adjustment representing non-monetary values such as luxury and environmental benefits. We calibrated the price adjustment for each segment to match initial model predictions with California's real 2016 vehicle market shares. With total costs calibrated, an incentive can be added to lower the cost of a selected vehicle type, which will cause a change in predicted vehicle market share. The change in market share is used to determine the change in demand for incentivized vehicles and the proportion of vehicle sales directly caused by the incentives program. Based on the EV demand caused by program, our model reports estimated EV sales caused by the program, program costs, and benefits associated with the program. The program costs include administrative cost, implementation costs, and total incentive amounts offered. The benefits include GHG emission reductions, health improvement due to reduced air pollution, and monetary benefits from increased electricity sales.

Market Segments

The model includes 95 vehicles organized into 30 vehicle segments based on size, class, and engine type - including internal combustion engine (ICEV), hybrid, plug-in hybrid electric (PHEV), and electric vehicles (EV). Where available, we chose the five top-selling vehicles from each segment, using data from the California New Car Dealers Association (Auto Outlook, 2017). The full list of included vehicles can be found in Appendix C.

Cost Estimates

The model assigns a total cost to each vehicle segment, and varies these total costs in Monte Carlo simulations. Costs for vehicle segments were assigned based on average costs for each vehicle within a given segment. Total direct costs for each vehicle were calculated as the sum of:

- **Purchase price:** national average of prices actually paid; from TRUEcar.com (n.d).
- **Fuel costs:** present value of fuel costs for the average car lifetime, using fuel economy data from fueleconomy.gov (n.d) and average annual vehicle miles travelled for Light Duty Vehicles from the Federal Highway Administration (2015). We used a discount rate of 20% as literature suggests that consumers undervalue these when purchasing vehicles (Dreyfus & Viscusi, 1995; Mannering & Winston, 1985; Gallagher & Muehlegger, 2011).
- **Remaining Ownership and Operating Costs:** Other ownership and operating costs were collected for each car model from edmunds.com (2017). These costs include:
    - **Maintenance and repair costs:** present value of average maintenance and repair costs for the average car lifetime, including batteries, brakes, tires, and so on;
    - **Depreciation:** present value of depreciated car price after the average car lifetime.
    - **Insurance, license, registration fees, and taxes:** present value of national average of costs for the average car lifetime.
    - **Financing costs**: present value of the average interest on a loan using a 10% down payment and a loan term of 60 months.

We calculate costs over a 7-year timeframe, which is the average length of ownership of a passenger vehicle (IHS, n.d.). We assumed PHEVs ran 40% on electricity and 60% on gas, in alignment with CARB Air Quality Improvement Plan assumptions (2016). For car models without available cost data, we used the costs of the most similar car model (see Appendix D). Depreciation rates for these cars were calculated as a proportion of purchase cost determined by comparison with depreciation of similar vehicles.

Across simulations, the model varies total purchase and ownership costs by randomly selecting from among the vehicles included in that segment, based on a vehicle's relative popularity within that segment. The model then adds the average purchase and ownership costs of the chosen vehicle to the total cost for the vehicle segment in that simulation. Average operating costs are held constant across simulations, based on the weighted average operating costs of vehicles in each segment.

Model Calibration

Including only purchase price and ownership and operating costs fails to capture the non-monetary values that influence a vehicle's perceived value, e.g. style preferences, range anxiety, and imperfect information flow. To incorporate these qualitative factors, we first ran the model including only the monetary cost factors. We compared the model's predicted vehicle market shares to California market share data for 2016 (AutoOutlook, 2017), then iteratively assigned additional perceived values to each segment to match model predictions with real market data.

Once calibrated, the model can be used to add incentives to EVs and PHEVs, which will modify their total costs and create a new predicted market share. From this change we predict the percentage of EV and PHEV sales attributable to the incentive using the equation:

$$Proportion\ Incentive\ Caused\ Sales = \frac{New\ Market\ Share - Baseline\ Market}{New\ Market\ Share}$$

We included additional inputs that users can manipulate to alter total vehicle costs, including:

- **Federal and State rebate availability:** By default, the model is set to reduce EV costs by the amount available from federal and state rebates. We included the option to remove these rebates to preserve the model's functionality if either rebate becomes unavailable.
- **Additional rebate amount:** Users can input additional incentives, such as those they have negotiated with manufacturers and dealers. These alter vehicle costs in the same way as agency provided incentives, but do not add to overall agency costs.
- **Include High End and Luxury EV and PHEV:** The model allows users to decide whether to include luxury EV and PHEV models among those eligible for incentives.

Predicting Incentives Used

The number of vehicle incentives used by agency residents can be limited either by the number of available incentives or overall demand for incentivized vehicles. To calculate number of available incentives, we require the user to input the overall incentives budget and incentive amount for EVs and PHEVs. To account for the possibility of distinct incentive amounts for EVs and PHEVs, we assume incentives will be distributed proportionally based on the predicted change in market share for each. For example, an incentive program resulting in predicted market shares of 4% for EVs and 2% for PHEVs, would assume a 2:1 distribution of incentives. The total number of available incentives is then calculated as:

$$Available\ Incentives = \frac{Total\ Incentives\ Budget}{(Proportion\ EV\ Incentives) x\ (EV\ Incentive) + (Proportion\ PHEV\ Incenvtives) x (PHEV\ Incentve)}$$

To predict overall demand for EVs among an agency's residents, we assume that vehicle demand is proportional to demand across California. We calculate vehicle demand as the total population served by a given agency multiplied the ratio of auto sales to population across California in 2016 (U.S Census Bureau, 2017).

$$Vehicle\ Demand = Agency\ Population\ x \frac{2016\ California\ Auto\ Sales}{2016\ California\ Population}$$

EV and PHEV demand are calculated by multiplying predicted market share for each by the total vehicle demand. Predicted number of incentives used is set at the lower of demand and available incentives.

We included in the model several ways for the user to alter EV and PHEV demand, depending on their program specifications. These include:

- **Program length:** The model calculates vehicle demand on an annual basis. Users can select the number of months that the program will run and demand will be altered proportionally (e.g. a 6 month program would result in half of the predicted demand compared to an identical 12 month program).
- **Leased vehicles:** The model allows users to select whether customers can receive incentives on leased as well as purchased vehicles. If leased vehicles are included, predicted demand increases with the assumption that 40% of vehicles will be leased. We believe this is a conservative estimate, based on the demand for leased EVs through California's Clean Vehicle Rebate Program, which has risen from 40 - 70% between 2012 and 2015 (Center for Sustainable Energy, 2017c). For all calculations of costs and impacts, we treat leased and purchased vehicles identically.
- **Marketing effectiveness:** How well an incentive program is advertised to customers influences overall program uptake (Stern, 1999; Maibach et al., 2008). This model does not capture the influence of marketing strategies on program uptake, which can vary widely. Users can input an estimate of their marketing effectiveness as a percentage of potential customers who are made aware of the incentive program. This estimate will directly alter the predicted overall vehicle demand.

Future Cost Projections

To allow agencies to plan incentive programs in the future, we incorporated cost projections for EVs for the years 2017-2030. This was done using cost projections from Bloomberg New Energy Finance which are based on projected decreases in EV battery prices (Soulopoulos, 2017). The model recalculates a baseline market share depending on the year the program is set to run, using these cost projections.

Smart Charging Program

We included an option for agencies to pair the incentive program with a smart charger program. Smart chargers can be controlled remotely by the agency to delay EV charging and reduce peak energy demand. To estimate typical charging behavior throughout the day, we use an average charging schedule from 27 PG&E customers who drive EVs and are charged a baseline electricity rate (Biviji, 2014). To estimate the effect of providing agency-controlled Smart Chargers, we allow the user to input electricity mix and rate information by time of day. The model assumes customers provided with Smart Chargers will not charge during peak times from 2-10pm. The amount of charging that would have occurred in that time period is then displaced to the hours from 10pm-4am.

EV Model Emission Calculations

Vehicle tailpipe emission factors are referenced from the California Air Resources Board (CARB) 2014 EMFAC database (California Air, 2014). The EMFAC database estimates emission rates (g/mile) for CO_2, NOx, SOx, PM10, PM2.5, total organics (TOG), and CO for all vehicle classes, for gasoline and diesel powered vehicles, at different speeds, for model and calendar years from 1965 through 2050. CH_4 and N_2O emission factors for passenger cars and trucks are referenced from EPA guidance documents for completing GHG inventories and are incorporated into their respective vehicle class emission factors (2015). Emission factors for model years 2008-present are identical and are assumed to be representative of the majority of available on-road vehicles. The EMFAC database allows users to select statewide, air basin, air district, MPO, county, or sub-area geographical boundaries. The analysis uses annual emission rate data for a selected model years (2017 through 2030), at aggregated speeds, and by air pollution control districts. Air pollution control districts overlay well with CCE agency jurisdictions and will likely face similar health impacts.

Emission factors (g/mi) are generated using a weighted average of gasoline and diesel emissions for different car classes according to the equation:

$$EF_{class} = \frac{(EF_{gas})(VMT_{gas}) + (EF_{diesel})(VMT_{diesel})}{VMT_{gas} + VMT_{diesel}}$$

where,

$EF_{class} = weighted\ emission\ factor\ for\ class\ of\ vehicle\ (\frac{g}{mi})$

$EF_{gas} = emission\ factor\ for\ gasoline\ fueled\ vehicle\ (mi)$

$VMT_{gas} = total\ vehicle\ miles\ travelled\ for\ gasoline\ vehicle\ (mi)$

$EF_{diesel} = emission\ factor\ for\ diesel\ fueled\ vehicle\ (\frac{g}{mi})$

$VMT_{diesel} = total\ vehicle\ miles\ travelled\ for\ diesel\ vehicle\ (mi)$

We assumed that people purchase EV or PHEV vehicles over comparable passenger car vehicle classes; therefore, we used the Light Duty Automobile (LDA) class emission factors from the EMFAC database to calculate the avoided conventional vehicle tailpipe emissions. PHEVs in the database are assumed to operate 60% on gasoline and 40% on electricity (California Air Resources Board, 2016).

We calculated the total emissions avoided for each vehicle type by multiplying each type's emission factors by the annual average vehicle miles travelled (VMT). We calculated that battery EVs have a weighted fuel efficiency of 0.3 kWh/mi. Following recent literature we added 3% in annual VMT to account for the rebound effect (Sun et al., 2017).

Results & Discussion

Summary of EV Model Major Findings

- **Low incentive amounts cause few new EV purchases.** The model predicted $500 incentives would largely subsidize individuals who would have purchased an EV even without the incentive program.
- **Incentives in the $3,000-$4,000 range were the most cost-effective** for reducing emissions, when added to federal and state incentives, in the test scenarios we modeled. The best value of an incentive amount will vary depending on program-specific inputs.
- **Incentives for EVs only, not PHEVs, were more cost-effective overall** for achieving GHG emission reductions than incentives offered for both EVs and PHEVs.
- **Health benefits alone are too small to justify offering incentives**, and can vary greatly depending on source electricity mix. Agencies with higher renewable content electricity mixes will see greater health benefits from EV rebates.
- **Marketing effectiveness can play a large role** in changing the predicted demand for incentives. Agencies should understand that a high marketing effectiveness input assumes a well-run, well-marketed program, of which constituents are aware and can easily take advantage.

The completed EV model allows users to predict the results of offering incentives on EVs, PHEVs, or both. The model reports the predicted number of vehicle purchases caused by the incentive and associated GHG and health benefits, and overall program costs. Users can input varying incentive amounts and compare the relative cost-effectiveness of each to achieve GHG emission reductions.

To demonstrate sample model results, we ran the model under a range of incentive amounts and present model predictions below. We used a $1.5 million incentive budget and a 3 month program length. Results were predicted for Sonoma County in 2016, assuming 100% marketing effectiveness and availability of both federal tax credits and CVRP rebates.

Effect of Incentives on EV Sales

Figure 1 displays the effect of changing incentive amount on predicted EV sales and the proportion of sales attributed to the incentive. At low incentive amounts, our model predicts most incentives will be redeemed by individuals that would have purchased EVs even without an incentive. As incentive amount increases, the proportion of incentive-caused EV sales appears to increase logarithmically, approaching but not reaching 100% of sales (Figure 1A). Demand for EVs increases as incentive amount increases, and results in greater total vehicle sales up until the point where the demand for vehicles reaches total number of available incentives, based on the set budget of $1.5 million (Figure 1B).

To cause the most EV sales, an incentive should be set at the amount that produces just enough demand to consume the available budget. Higher incentives will result in fewer new vehicles, as an agency would be spending more for each incentive and depleting its budget sooner. Under this test scenario, the total incentives budget is predicted to be used with a $4,000 incentive per vehicle. Raising the incentive amount past this point results in fewer available incentives.

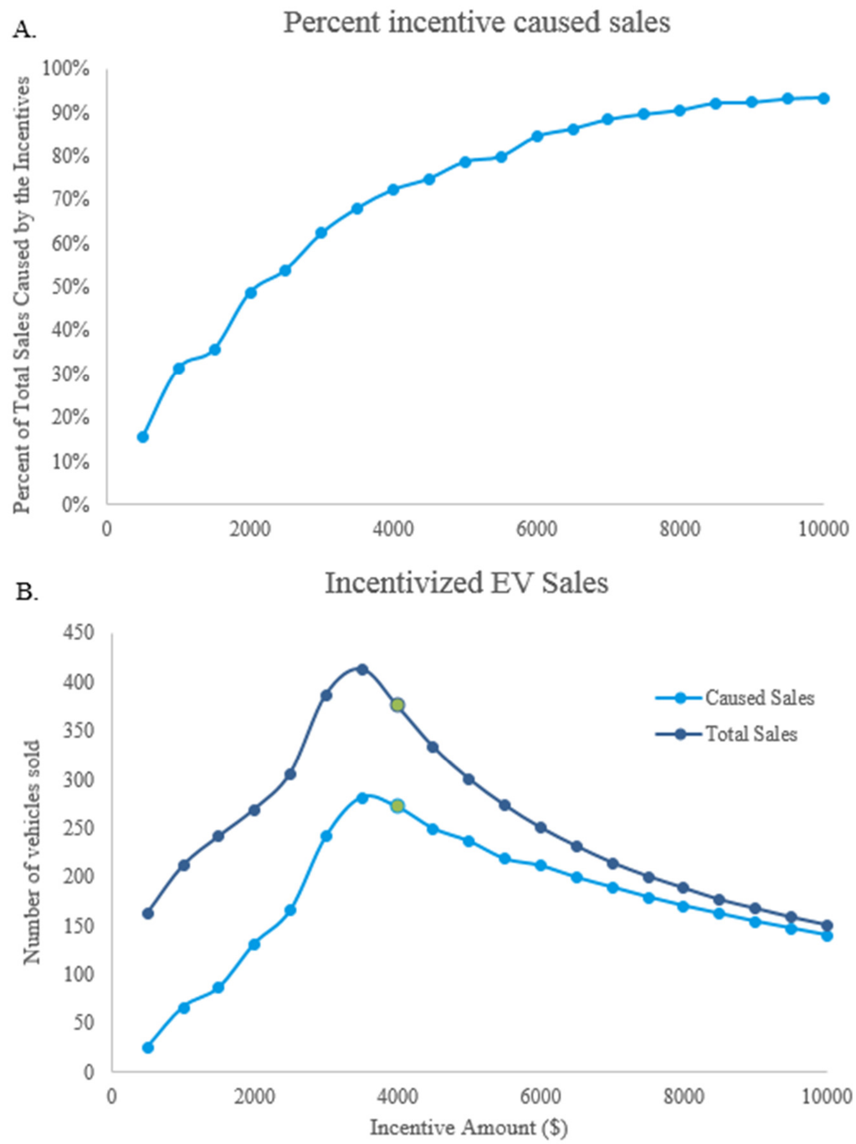


Figure 1. Effect of incentive amounts from $500 to $10,000 on A) percent of sales attributable to the incentive, and B) total EV sales resulting from the program, compared to incentive-caused sales. Green points indicate the lowest incentive that results in sufficient demand to use the entire incentives budget.

<u>Potential for Incentive Targeting</u>

There is the potential to expand this model to inform more efficient targeting of incentives. The TCM structure can simulate an individual's perceived cost for each purchase option. For each simulation, the model can therefore give the theoretical exact incentive amount necessary to make an EV the lowest cost option, as the cost difference between the lowest cost vehicle overall and the lowest cost EV. This could be used to estimate the excess spending associated with a given incentive amount, by comparing it to the lowest amount necessary to cause an individual to switch to an EV.

Optimal incentive values likely differ with depending on target audience, such as low- and high-income customers. Identifying these audiences could improve the efficiency of incentive targeting, but this is beyond the current capacity of our model. To calibrate the EV model based on distinct audience needs, we would need existing market data for each target audience. This could be a potential direction for further research and expansion of TCM applications.

Effect of Incentives on Greenhouse Gas Reductions

Figure 2 displays model predictions for GHG emission reductions and the cost of achieving those reductions depending on incentive amount for EVs and PHEVs. Total GHG emission reductions peak at a $3,500 incentive for EVs, and at a $2,500 incentive when the incentive is available to both EVs and PHEVs. The cost to reduce each ton of CO_2e is lowest for incentives in the $1,500 to $3,500 range. At lower incentive amounts, a greater proportion of incentives go to individuals who would have purchased an EV or PHEV regardless of the incentive program. These vehicle sales do not contribute to the GHG emission reductions caused by the incentive program and lead to a less cost-effective program. Results in Figure 1 showed that the proportion of incentive-caused vehicle sales rises quickly as the incentive increases from $500 to $3,500. Raising the incentive amount within this range, therefore, reduces the cost per ton of GHG emission reductions, as proportionally more EVs sold are attributable to the incentive program.

As the incentive amount is raised past this point, the cost to reduce each ton of CO_2e increases. This is due in part to set budget limitations, as the same amount is spent on fewer overall sales, and to the change in the proportion of incentive-caused sales at higher incentive amounts. As the incentive amount increases, the change in percent incentive-caused sales levels off, resulting in diminishing returns for GHG emission reductions with higher investments in incentives.

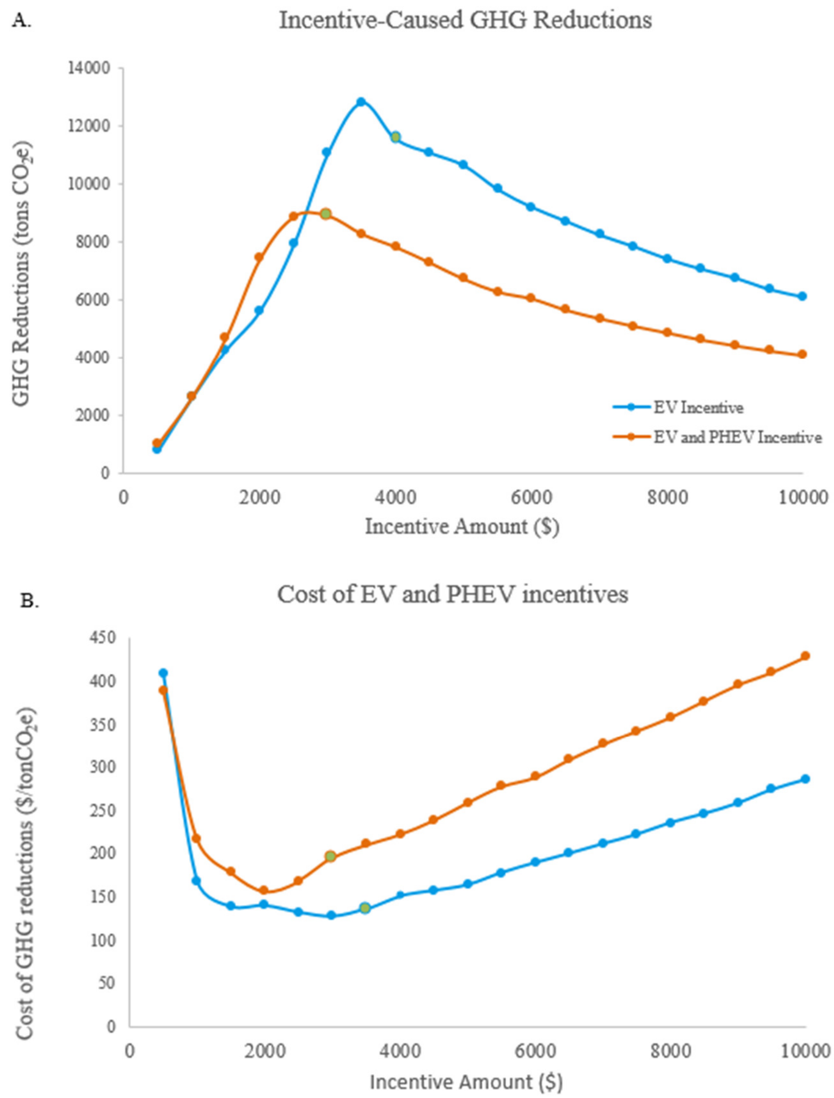


Figure 2. Effect of a range of incentives from $500 to $10,000 on A) total predicted GHG emission reductions from the incentive program, and B) cost-effectiveness of GHG emission reductions, for incentives applied to EVs only (blue) and to both EVs and PHEVs (orange). Green points indicate the lowest incentive amount that results in sufficient demand to use the entire incentives budget.

Except at the lowest tested incentive amount of $500, applying an incentive to both EVs and PHEVs resulted in more spending per ton of GHG emission reductions than applying the same incentive to only EVs. At incentive amounts below about $3,000, a combined EV and PHEV incentive resulted in comparable or higher total GHG emission reductions. This is because the larger selection of eligible vehicles increases overall demand for incentivized vehicles. As a result, a lower incentive can produce enough demand to use the entire incentives budget. At higher incentive amounts, EV-only incentives caused greater GHG emission reductions. With an appropriately set incentive, EV-only incentives have a greater overall GHG reduction potential than incentives for both vehicle types.

In the literature there are a wide range of estimates for the cost of GHG emission reductions achieved by incentivizing EV and hybrid vehicles (Chandra et al., 2009; Michalek et al., 2011; Plotkin and Singh, 2009). Our model predicts a range of GHG reduction costs, depending on incentive amount, type of incentivized vehicle, source electricity mix, and other user inputs. Our model results generally fall within the range of cost estimates from the literature, suggesting a well executed incentive program could cost $120-$150 per ton CO_2e reduced, whereas a poorly set incentive could result in a cost of several hundred dollars for each ton of CO_2e reduced.

Drive EverGreen Test Runs

To validate our model, we compared our predictions to results from a real-world EV rebate program. We ran our model twice using specifications from Sonoma Clean Power's (SCP) 2016 and 2017 Drive EverGreen EV incentives programs. We set marketing effectiveness at 100% to clearly demonstrate our model predictions, although this is an unrealistic assumption that produced exaggerated results. For both the 2016 and 2017 programs, our model over predicted incentive demand compared to real-world results. However, our model predictions for the cost of GHG emission reductions through these programs matched closely with the analysis performed by SCP. Below, we discuss detailed model results and their implications.

Inputs and Results Overview

Table 3 compares Drive EverGreen 2016 program specifications with the inputs we used to model the program. SCP offered $2,500 rebates to customers who purchased or leased a qualifying EV. A $5,000 rebate was offered to qualifying low-income customers. Our model does not have the capacity to offer incentives of different values to certain customers, so we used only the $2,500 incentive for the test. The other model inputs matched SCP's program. SCP had an overall incentive budget of $1.5 million. SCP also negotiated additional discounts of $10,000 on qualifying purchases from participating EV dealers, which did not add to SCP costs. The program ran for three months and supplied 206 incentives for leased and purchased vehicles. SCP estimated spending at $56 per ton of CO_2e emissions avoided as a result of the program, excluding program administrative costs. The model predicted 600 redeemed incentives over the 3-month program, the maximum possible with the program budget. Of the sales associated with an incentive, 96% were attributed to the incentive.

Table 3. Model Results for SCP Drive EverGreen 2016 Program

INPUTS		
	Drive EverGreen 2016	**Model Input**
Agency (Region)	Sonoma Clean Power	Sonoma
Incentives Budget	$1,500,000	$1,500,000
Incentive Amount BEV	$2,500, $5,000 for qualifying low-income customers	$2,500
Incentive Amount PHEV	None	None
Additional Discount	$10,000	$10,000
Program Length	3 months	3 months
OUTPUTS		
	Drive EverGreen 2016	**Model Output**
GHG Emission Reductions	10.6 M tons	25.7 M tons
Certificates Approved	511	NA
Incentives Used	206	600
Proportion of Sales Caused by the Incentive	88%, according to survey responses	96%
Cost per ton CO_2e Reduced		
Incentive and admin costs:	Not reported	$68
Incentive costs only:	$56	$58

SCP ran its Drive EverGreen program again in 2017 for four months. This time, SCP offered $2,000 incentives, and $3,500 incentives for qualifying low-income customers. SCP also negotiated manufacturer discounts of $8,000 (Center for Sustainable Energy, 2018). Table 4 compares Drive EverGreen 2017 specifications with our model inputs and selected results.

Table 4. Model Results for SCP Drive EverGreen 2017 Program

INPUTS		
	Drive EverGreen 2017	**Model Input**
Agency (Region)	Sonoma Clean Power	Sonoma
Incentives Budget	$1,500,000	$1,500,000
Incentive Amount BEV	$2,000, $3,500 for qualifying low-income customers	$2,000
Incentive Amount PHEV	None	None
Additional Discount	$8,000	$8,000
Program Length	4 months	4 months
OUTPUTS		
	Drive EverGreen 2017	**Model Output**
GHG Emission Reductions (CO_2e)	Not reported	30 M tons
Certificates Approved	1,354	NA
Incentives Used	565	750
Proportion of Sales Caused by the Incentive	Not reported	93%
Cost per ton CO_2e Reduced		
Incentive and admin costs:	Not reported	$60
Incentive costs only:	Not reported	$50

Model Validation using Cost of GHG Emission Reductions

Our two model runs and SCP produced comparable estimates for overall cost-effectiveness of GHG emission reductions, with our estimate and SCP's differing by $2 per ton of CO_2e reduced, less than 4%, after excluding administrative costs. SCP estimated the pilot programs' GHG reduction results using survey data to determine which vehicles customers would have driven had they not been offered incentives for an EV. They compared the estimated emissions from this counterfactual set of vehicles with those estimated from the set of vehicles including the incentive-caused EV purchases to predict the change in emissions. SCP calculated the cost to reduce each ton of GHG emissions using only the cost of the incentives provided, excluding administrative costs.

We believe SCP's methodology of estimating the cost per ton of GHG emissions avoided is robust because the survey data created a reasonable approximation of the vehicles that would have been driven had there been no rebate program. In addition, we believe the basic design elements of the Drive EverGreen pilot programs will probably become standard for EV incentive programs, as the pilots were quite successful and other CCE agencies will likely pattern their programs after these first ones. Due to these factors and the close match between our model's outputs and SCP's, we believe that our model can produce cost per GHG reduction estimates that are reasonably close to the true values. By customizing inputs including program design, population, and energy mix to those relevant to their agencies, future users can use this model to produce reasonable predictions for the results of their own programs.

A key difference between the model tests using Drive EverGreen inputs and the other model test runs described in these results was the addition of substantial manufacturer incentives (included in the model as "additional incentives"). These incentives drive up demand for EVs without increasing costs to the agency, resulting in improved cost-effectiveness of GHG emission reductions. The model predicts a cost of $50 per ton CO_2e reduced for the $2,000 agency incentive and $8,000 additional incentive offered by the Drive EverGreen 2017 program. Running the model instead with a $10,000 agency incentive produces a cost of $285 per ton CO_2e reduced. Surveys conducted among EV dealers following the 2016 Drive EverGreen program suggested a high degree of dealer satisfaction with the incentive program. Given our predictions of incentive-caused EV purchases with high incentives, it is reasonable to expect that dealers and manufacturers who work with CCE agencies to offer incentives will also benefit from increased sales that result from the offering.

Demand for Incentives

For both the 2016 and 2017 programs, our model predicted sufficient demand to use all available incentives over the length of the programs. In reality, only about one third and two thirds of available incentives were redeemed for 2016 and 2017 respectively, though more residents applied and were approved for incentives than ended up redeeming them. In addition, our model tests did not include the higher incentives offered to low-income residents, which would have increased predicted demand further.

This over prediction of demand could be the result of our assumptions of perfect marketing effectiveness. The model was run with marketing effectiveness set at 100%, which assumes all eligible residents were made aware of this program. Surveys conducted among 2016 Drive EverGreen participants suggest many participants were confused about the types and amounts of available incentives (Center for Sustainable Energy, 2017c). This would have had a particularly strong influence on overall demand if customers were not made aware of the large additional incentives offered by EV dealers. In addition, for the 2016 program, only two vehicles were eligible for incentives: the Nissan Leaf and BMW i3. A number of survey respondents who did not redeem an incentive reported this lack of choice as a limiting factor. For the 2017 program nine vehicles were eligible for the incentive, so this was likely less of a limiting factor for incentive customers.

Modulating the marketing effectiveness parameter to 5% for 2016 and 20% for 2017 produces similar predictions to empirical results. These tests reveal the powerful nature of the marketing effectiveness parameter in this model. Users should be aware that running the model with high or perfect marketing effectiveness will produce results that represent a highly well executed incentives program, where eligible residents have a clear understanding of available incentives and few other barriers to acting on this knowledge.

Health Impacts of EV Incentives

We found that health benefits from EV incentives are small compared to the overall costs of an incentives program, even considering the large uncertainty associated with the value of pollutant reductions. To produce sample results, we ran the model using SCP's CleanStart energy mix and a $3,000 incentive, and calculated impacts for Low, Medium, and High estimates of pollutant values on health impacts. Results are presented in Table 5. The highest estimates for value of health impacts produce health benefits of $69,000 over the life of the incentivized vehicles, equal to roughly 5% of total program costs. The lowest estimates produce benefits totaling 0.02% of total costs. Even with the large uncertainty in health benefits the difference between the high and low values is not enough to change the overall benefit-cost ratio of the program much. Reducing total program costs by the value of health impacts can slightly improve the calculated cost effectiveness of GHG emission reductions. In this scenario, the highest estimate for health benefits reduced cost of GHG reduction by $8 per ton CO2e.

Table 5. Health benefits associated with a $3000 EV incentive program set in Sonoma County using a range of health impact values.

Value of Health Impacts	Program Health Benefits	Total Program Costs Minus Health Benefits
Low	$3,032	$1,364,617
Mid	$28,865	$1,350,739
High	$68,957	$1,313,666

These benefits are dependent on the electricity mix that supplies incentivized EVs, and can be negative if the mix is not clean enough. This suggests that an agency should first procure a sufficiently renewable energy mix before incentivizing EVs, to avoid worsening health impacts relative to driving conventional vehicles.

These benefits were calculated by treating a ton of pollutant equally, regardless of location of emission. This does not capture important aspects of real-world emissions impacts. When predicting health impacts from pollutant emissions, agencies should consider the location of electricity generators and the areas they expect new EVs to be driven. Model estimates are presented as a rough approximation of health impacts that can result from an incentive program.

Model limitations

TCM attempts to account for qualitative factors that influence consumer decisions, but there are aspects of the EVs market that may not be captured here. Availability of charging stations, vehicle perception, and vehicle range on a single charge all influence EV sales (National Research Council, 2015). This model is designed to consider these in the perceived value component of cost calculation, but does not account for change in perceptions over time or local variability. As new EVs are developed and perception of EVs changes, this model will need to be recalibrated to reflect the change in total value. This requires manually altering the perceived values for each vehicle segment to match the desired baseline market share, a process that a toolkit user can do but that can take up to hour.

This model does not consider purchases timed to fit into the incentive schedule, i.e. purchases that would otherwise have occurred earlier or later but were instead made to coincide with incentive availability. This should not interfere with model predictions for the proportion of incentive-caused purchases, but may result in a larger number of vehicle purchases than predicted.

One potential benefit of incentive programs not captured by this model is the network effect associated with EV sales (Winebrake and Farrell, 1997). As more people are seen purchasing and driving EVs, others will be encouraged to make similar purchases.

CARB's EMFAC database suggests that EV purchasers drive more miles per year than our model input (California Air Resources Board, 2014). If this is the case, our model may underestimate the environmental benefits of EV incentive programs. Our model calculates vehicle emissions based on average annual miles driven in the United States. If more frequent drivers replace their ICEVs with EVs, there will be greater emissions reductions per vehicle.

Solar Photovoltaic Financing Program

Background and Overview

Based on interest from agencies and a suggestion from our client, we created a TCM to predict the uptake of residential rooftop solar PV if agencies were to back low interest financing programs. This section of the report provides background on existing solar PV financing options and the potential role for CCE agencies to provide their own financing options.

Role of Financing in the Solar Market

With the average cost of a residential solar photovoltaic (PV) system ranging between $15,000 and $35,000, most people cannot purchase a system upfront; instead, they opt for a financing option to cover the cost of their system or the electricity that they get from PV (Hausman, 2015). In fact, the rapid growth of the residential solar market can be largely attributed to the widespread availability of diverse solar financing options (Litvak, 2015).

Types of Financing

There are four general types of solar financing available in California: loans, PACE financing, leasing, and power purchase agreements. Solar loans and PACE financing give the customer ownership of the system along with any government incentives, whereas a third party entity owns and maintains the system in the latter two options (Hausman, 2015). Each option causes different levels of increased public participation in the solar market and financial security for the lenders. CCE agencies can choose from among these types or structure a product that borrows from multiple types when deciding how to design their own solar financing programs.

Solar Loans

As with loans for other goods, there exist a variety of loan offerings that differ in credit requirements, interest rates, and monthly payment amounts. Lenders can be banks, solar companies, utilities, and other private solar financing companies (Hausman, 2015).

There are two types of solar loan products: secured and unsecured loans. Secured loans require that the customer put up an asset, such as a car or house, as collateral for the loan in case of default. Unsecured loans do not require any collateral, but because of this, they tend to have higher rates and shorter repayment periods than secured loans (Greenpath, n.d.). The drawback of solar loans is that their availability is limited to people with a minimum FICO credit score of about 650 to 700, which is in the acceptable to good range (DiGangi, 2015). This excludes homeowners with subprime credit scores from the possibility of owning a solar system, and also prevents them from benefiting from government incentives.

PACE financing

PACE, or Property Assessed Clean Energy, financing is repaid through an addition to the owner's property tax bill. The financing is provided to property owners who agree to place a special tax assessment for the amount financed on their properties, making these effective collateral for the financing. There are no credit requirements, although each PACE program has other property owner and project eligibility requirements to make repayment more likely (Kaatz & Anders, 2014). PACE financing is widely available throughout California and has been found to increase the solar PV installation rate over the background rate (Kaatz & Anders, 2014; PACE in California, 2017; Ameli et al., 2017).

The lack of credit requirements allows more people access to financing at a reasonable interest rate than before. The advertising of the PACE program and its association with the local government have been proposed to lower information costs, as prospective customers a) become aware of the program and b) feel less need to research it further because of the trusted government aspect (Kirkpatrick & Bennear, 2014; Ameli et al., 2017). Another favorable aspect of PACE is that a property owner can legally sell the property and pass the payment responsibility on to the next owner (Kirkpatrick & Bennear, 2014). However, this is not always possible due to federal policies, and the risk of having to repay the remaining amount before selling keeps some people from using PACE financing, possibly canceling out this advantage (Kaatz & Anders, 2014; Gerdes, 2017).

Solar leasing

In solar leasing, the leasing company retains ownership of the system along with the government incentives that come with it. The customer enters a contract with the leasing company to pay a regularly scheduled payment in return for the installation and maintenance of the system in addition to the electricity generated by the system. A typical lease term is about 15 to 20 years (Hausman, 2015).

Solar leasing used to be the most popular financing option for solar PV systems, accounting for the majority of the national market share. However, the market in the U.S. and California has experienced a significant decline in third-party owned solar beginning in 2016. The market share for third-party ownership, which peaked in California at 75% in 2013, has since dropped below

36% as more people have opted to purchase rather than lease PV systems (Litvak, 2017). The shift from leasing to buying solar panels has been attributed to the declining cost of panels as well as the government rebates and tax incentives that only come with direct ownership of the PV systems (Mearian, 2016).

Leasing as a financial mechanism faces a similar disadvantage as loans in that there is generally a minimum credit requirement that excludes those with lower credit scores from accessing solar energy. In fact, the CEO of SolarCity, one of the largest solar leasing companies in the United States, stated that he did not intend to lower the minimum credit score requirement below 650 in the next few years (Reuters, 2015). Again, this poses an issue for homeowners with subprime credit who potentially would like to install PV for their homes.

Power Purchase Agreements

Power Purchase Agreements, or PPAs, operate similarly to solar leasing where the financing company installs and maintains the solar PV system on the homeowner's property, but instead of regular scheduled payments on the system, the homeowner pays a fixed rate based on the amount of electricity used. This rate is generally set at a level guaranteeing the customer cost savings over electricity from the utility company. As with solar leasing, PPAs exclude the customer from government tax credits, which go to the system owner. PPAs are a less popular option than solar loans or leasing due to their greater complexity (Hausman, 2015).

Potential Roles for CCE Agencies

Although there are already many companies providing financing for PV systems, opportunities still remain for CCE agencies to use their specific advantages to increase the size of the residential PV market. Some of these advantages are the agencies' not-for-profit missions, the trust they command as government entities, their ability to publicize programs, and their existing billing relationships with their customers. CCE agencies can enter PV financing by creating new in-house financing products or by endorsing and coordinating with existing financing companies. Depending upon a program's design and interest rate, it can be an inexpensive or even value-generating option for agencies.

CCE agencies may have the ability to provide or back financing at lower interest rates than some companies because the agencies are not profit-driven. In order to reduce risk and maximize profits, many existing lenders have credit score minimums that exclude consumers with low credit scores or incomes, or offer them prohibitively high interest rates. By offering affordable financing, CCE agencies can expand access to these community members, who form a significant untapped PV market, as shown by the increase in PV uptake seen in areas with PACE financing. This would amplify a recent widening trend in PV buyer demographics, helping achieve the elements of many CCE agencies' missions to increase renewable energy usage while decreasing costs (Patel, 2017). Two options for including lower-income or lower-credit individuals while protecting the lender include the property- and project-based eligibility requirements of PACE financing and the creation of a loan loss reserve fund, which compensates the lender for any defaults that occur (Menten and McNeil, 2016).

CCE customers may be more inclined to trust the CCE agency than a private lender because of both the agency's status as a not-for-profit government agency and their established relationship with the agency as an electricity supplier. This trust can be leveraged to increase customers' willingness to use the financing product and any solar installer the agency may choose to endorse. An NREL report showed that larger, more popular solar companies were on average more expensive than smaller, more local installers, who tended to be more responsive to market conditions and policy changes, and more likely to provide fair pricing on their systems (O'Shaughnessy & Margolis, 2017). Thus, a wise strategy for agencies trying to minimize installation costs might be to partner with local installers.

Any financing program publicity endorsed by the agency will be more effective due to viewers' trust of the agency. The agency can publicize the program in its monthly bills, increasing the reach to the entire agency ratepayer population and/or targeting specific high energy using groups. The agency can also simplify the loan repayment process by allowing on-bill repayment, which allows customers to pay back loans through additional payments on their monthly electric bills. Currently, some utilities offer on-bill repayment to commercial and municipal customers. By extending this model to residential customers, CCE agencies could provide a simple and convenient method for them to pay back solar loans (Hausman, 2015; Center for Sustainable Energy, 2015).

Methods

Model overview

We constructed a model using the TCM framework to predict the direct impact of lowered interest rates on the number of residential solar photovoltaic (PV) system installations. The model predicts the market share of grid electricity, customer-owned PV, and third-party-owned PV based on their cost and a cost adjustment representing customer resistance to buying PV. The market share segments represent the percentage of households with roofs eligible for new PV systems that choose each of the above three electricity sources in a given year. Net Energy Metering (NEM) credits and payments reduce the cost of PV.

Interest rates can be adjusted to lower the cost of PV, which will cause a change in electricity source market share. By limiting the modeled program design elements to interest rate - not specifying whether the CCE agency funds financing for PV sales, hosts a private company that finances PV sales or third-party owned systems, or pursues another program design - we keep the model usable for any of these financing types.

Market share calculations

We estimated that 74% of roofs were suitable for PV because Gagnon et al. (2016) calculated that rooftop solar could replace that amount of the electricity sold by utilities in California in 2013. Furthermore, Google's Project Sunroof (2017) estimated that 87% of California and 86% of Sonoma County (as a regional example) roofs were suitable for PV. Google's estimates might be biased upward because they exclude economic considerations and some roof and building limitations, but they might be biased downward because they exclude systems outside the range of 2 to 1,000 kW as well as the possibility of mounting panels not flush with the roof (Google, 2017). Thus, we think these estimates are on the higher end of what is realistic.

We estimated baseline 2016 market shares of our three electricity source choices, for comparison against the market shares under lowered solar financing interest rates. This will need to be adjusted in future years by users, who can use the following methods. We first estimated the number of houses suitable for PV using the equation:

$$Suitable\ Houses\ in\ 2016 = (\#\ Houses)x(\%\ owner\ occupied)x(\%\ suitable) - (\#\ Houses\ with\ PV)$$

where,
 # houses = The total number of houses in an agency territory, estimated with data from the U.S. Census Bureau (2017)

% owner occupied = The percent of houses that are owner occupied and thus eligible for agency financing, estimated with data from the US Census Bureau (2017)

% suitable = The percent of houses that have rooftops suitable for solar PV. We used 74% for this value, based on estimates by Gagnon et al. (2016) and Google's Project Sunroof (2017)

 # houses with PV = The number of houses with existing PV systems in 2015. These were taken from the NEM California Distributed Generation Statistics dataset (2017) by filtering the data to include only the houses which matched relevant criteria explained in Appendix E.

To estimate the percent market share for new PV installations, we divided the number of 2016 residential PV installations from the NEM dataset by the total number of suitable houses in 2016. The result was divided between customer- and third party-owned PV systems using the ratio between these in the NEM dataset. We subtracted the total percent PV market share from 100% to get the grid electricity market share.

Electricity Usage and PV Generation Calculations

We calculated the standard deviation of residential electricity usage using the frequency of different monthly average consumption amounts found by Ayompe and Duffy (2013). We think this is reasonable because the distribution of PV system sizes, which generally track electricity usage, in the NEM dataset is similar (Figure 3). As such, our modeled electricity consumption is based on a log-normal distribution similar to the one they constructed in their study.

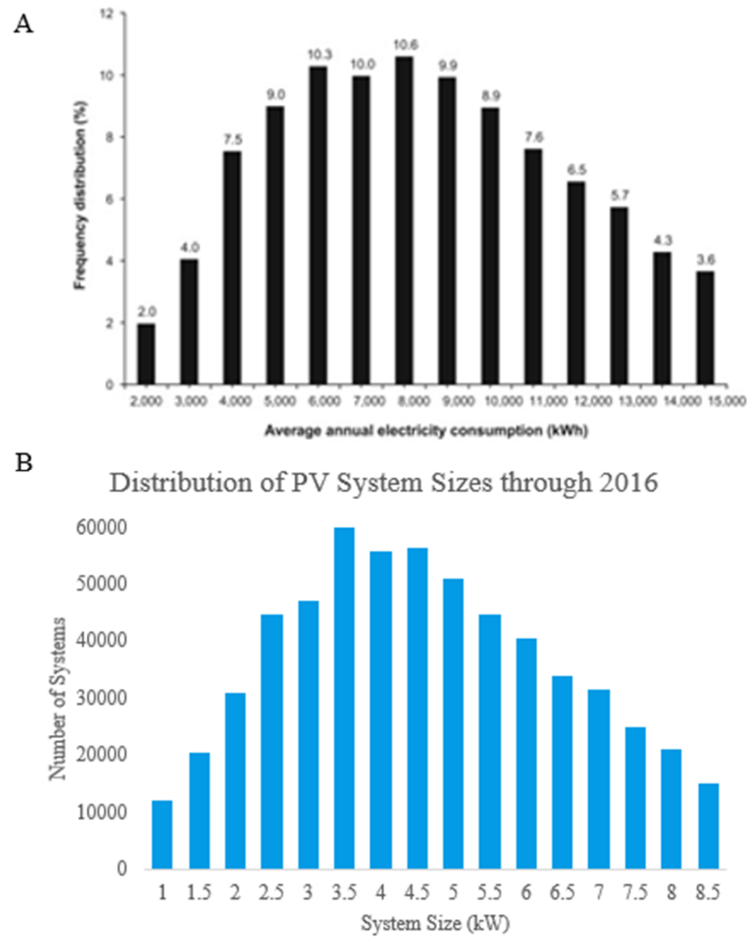


Figure 3. Distribution of A) electricity usage reproduced from Ayompe and Duffy 2013 and B) PV system sizes in CA from the NEM dataset.

However, our modeled electricity consumption is distributed around the mean monthly electricity consumption for each agency, as displayed on their web pages (Sonoma Clean Power, n.d., for example) comparing their residential rates with those of their respective IOUs. Toolkit users will be able to edit the mean value if desired. We restricted the maximum energy usage to 3,000 kWh per month to avoid outliers.

We modeled PV electricity generation per month as a left-skewed distribution around a user-input percentage of the electricity consumption that the PV should cover. We chose this distribution assuming that more PV buyers size their systems below their usage level, and to a greater degree, than above it. This is partially because residential PV in many areas is only supposed to be sized a maximum of 0-10% above a buyer’s usage (PG&E, 2017, Southern California Edison, n.d.).

We calculated PV system size using the equation:

$$Size = \frac{Generation\left(\frac{kWh}{month}\right) x \frac{12\ months}{year}}{8760\frac{hours}{year} x\ Capacity\ Factor}$$

Where the capacity factor is 20%. We used the electricity usage, PV generation, and system size amounts to calculate the costs described below.

Grid electricity cost calculations

A rate schedule is the set of rates under which a customer's electricity usage is charged, and can depend on the amount of electricity used in a month, the time of usage in a day, or other factors. The cost of grid electricity ($/kWh) from the CCE agency is entered by the toolkit user as three electricity rate schedule categories and the percentage of accounts in each category. The rate schedule categories are:

- **Most popular rate schedule:** e.g. the E-1 rate schedule for agencies within PG&E territory. This usually covers a majority of customers.
- **CARE:** the rate schedule for low-income customers.
- **Other:** typically comprise under 10% of customers. The user can enter a weighted average of the cost per kWh of the other rate schedules in this field.

The model chooses from among the grid electricity rates entered as inputs, with frequencies according to the percentage of accounts on each rate schedule. The rate is multiplied by each simulated usage amount to get monthly electricity bill amounts. The monthly amount is then multiplied by the number of months in the user-input PV lifetime being modeled, incorporating a user-input electricity rate escalator and discount rate. Specifically, the model calculates yearly amounts by multiplying the number of months per year, and then sums escalated and discounted yearly amounts by each year to find the net present value (NPV) of paying for electricity from the grid for the lifetime of a PV system. The equation is as follows:

$$NPV\ of\ Electricity\ Costs = \sum_{t=1}^{PV\ lifetime} \frac{Yearly\ Amounts(1 + Escalator)^t}{(1 + Discount\ Rate)^t}$$

PV monthly electricity cost calculations

The monthly solar financing payment amount for each simulated customer was calculated using the PMT function in Microsoft Excel, which determines the amount if a constant stream of payments is made, with a given payment frequency, payment duration, and interest rate. The PMT function requires the following inputs: interest rate, number of payments, and principal (excluding interest).

- The interest rate is adjustable by the user. It is varied using an adjustable standard deviation to represent variation that can occur between customers who, for example, have differential access to financing due to low credit scores, or value other aspects of a lender.
- The total number of monthly payments is determined by the financing payback period, also adjustable by the user, and assumes that payments are made monthly.

- The principal value is the capital cost of the PV system based on its size, which is determined as described above, and cost per kW.

The cost per kW is calculated by multiplying the modeled system size by the agency-specific average observed cost per kW for that system size from the website Solar Reviews (n.d.). Then the cost is varied using a standard deviation of around 20% to represent the variation that can occur between customers who, for example, negotiate different prices with installers or have different roof characteristics. This standard deviation value was chosen to approximate those observed in recent solar prices among some of the counties with the largest numbers of PV installations (California Distributed, 2017).

<u>NEM credits and payments</u>

Net Energy Metering (NEM) is a billing system in which any excess PV energy generated is credited back to the customer. Credits are provided at a $/kWh rate determined by the agency, often equal to the agency's retail rate for electricity and sometimes with a bonus payment, e.g. $0.01/kWh. We assume that all PV customers will participate in NEM, and that credits equal each customer's otherwise applicable rate schedule (OAS), as is the case with most agencies. The user inputs the bonus payment rate, as well as the average percentage of over-generation per month among the agency's customers. Any excess energy generated by a simulated PV system per month is multiplied by the sum of the credit and bonus payment rates per kWh. Any deficit is multiplied by the customer's credit rate and becomes a negative value in the NEM column.

<u>PV system lifetime cost</u>

The total cost of the customer- and third party-owned PV systems is calculated by summing the monthly cost, operating & maintenance cost, NEM value, and the perceived cost calculated as in the "model calibration" section below. The sum is discounted over the expected lifetime of the PV system and an IOU-specific interconnection fee is added (California Public, 2017). The resulting lifetime costs are compared to each other and the grid electricity PV lifetime cost to find the lowest total cost purchase option. The model runs through 100,000 simulated customers to determine what percentage of customers would choose each electricity source depending on which total cost is lowest.

Model calibration

The model determines the lowest total cost option, accounting for non-monetary perceived costs of purchasing or leasing PV. These perceived costs depend on the individual and might include the time and effort required for the purchase, decreased aesthetic value of their house, and other knowledge or preparation required for having a system. We calibrated perceived costs to match modeled market share with observed market share data under the agency's existing conditions. Once calibrated, the model can predict a change in market share that is caused by lowered PV financing interest rates.

CCE Agency Financing Program Effect

The monthly cost and lifetime cost calculations are repeated for customer-owned PV with the interest rate proposed for the agency financing program. The model assumes that:

- Customers who would previously have gotten an interest rate lower than the proposed one will stay with the lower rate.
- Customers who would previously have gotten an interest rate between the proposed rate and the previous average interest rate will qualify for and use the agency program.
- Customers who would previously have qualified only for an interest rate higher than the previous average interest rate will qualify for and use a rate reduced by the difference between the previous and agency program rates.

Comparing the new customer-owned PV lifetime cost with the baseline grid electricity and third party-owned lifetime costs over 100,000 simulated customers results in a new proportion of customers choosing each electricity source. The difference between the old and new market shares of the different electricity types is the additional PV uptake caused by the program.

Marketing Effectiveness

It is unlikely that 100% of the people for whom the program would be beneficial will hear of it. Therefore, a toolkit user can decrease the percentage of PV buyers who use the CCE agency solar financing program, in order to more accurately reflect the extent of the agency's marketing efforts or other factors in program success. The model then predicts a proportional number of program participants the agency should anticipate. For example, if the toolkit user predicts that their program marketing efforts will reach 10% of people considering solar, the user can enter 10% and the predicted change in market share will be multiplied by that amount.

Calculation of Model Outputs

Program effects

The percentage of houses participating in the agency program is determined by the equation:

$$\%\ Houses\ Participating = \%\ Buyers\ Using\ Program\ x\ Predicted\ PV\ Market\ Share\ with\ Program$$

Within the percentage of houses participating, there will inevitably be customers that would have purchased a solar PV system even without the agency's program. These participants' purchases cannot be attributed to the program, and should be excluded when quantifying the purchases directly caused by the agency financing program. This is calculated using the equation:

$$\begin{aligned}&\%\ Houses\ Participating\ due\ to\ Program\\&\qquad = \%\ Buyers\ Using\ Program\ x\ (Predicted\ PV\ Market\ Share\ with\ Program\\&\qquad - Observed\ Market\ Share)\end{aligned}$$

The percentage of houses purchasing PV due to the financing program can be multiplied by the total number of suitable roofs within the agency's jurisdiction to calculate the number of houses purchasing PV due to the financing program.

Costs

The toolkit reports three main sources of financial costs to the agency:

1) The major direct cost is the principal amount from providing loans to customers. This is calculated by summing the financing amounts of all the simulated participants in the program.

2) A more minor direct cost is the annual program administrative cost, which is entered by the toolkit user.

3) The indirect cost is the electricity supply revenue lost due to program-caused switching from agency electricity supply to customers' PV system-generated electricity. This is estimated using the equation:

$$Revenue\ Lost = Degradation\ x\ Generation\ x\ Participation\ x\ Avg\ Rate\ x\ \%\ Revenue$$

where,

Degradation = Sum of discounted degradation across PV lifetime of 25 years, accounting for solar degradation and incorporating customer discount rate, calculated as:

$$Annual\ Discounted\ Degradation = \frac{Annual\ Panel\ Degradation}{(1 + Customer\ Discount\ Rate)^{year}}$$

Participation = program-caused PV installations

Generation = average annual electricity generated by customers' PV systems

Avg Rate = average electricity rate charged to customers by agency for agency supply

% Revenue = the % net revenue margin from electricity sales

NEM bonus = average bonus payment offered to PV own customers

<u>Benefits</u>

The quantified benefits from the agency's solar financing program are presented by the toolkit as three broad categories: 1) greenhouse gas emission reductions, 2) health improvement, and 3) revenue from interest and principal.

1) Greenhouse gas emissions reductions: the benefits of greenhouse gas emissions reductions are presented as the amount of greenhouse gas emissions avoided, and the monetary benefits from these avoided emissions based on the value of carbon to the agency.

The emissions avoided across the lifetime of the PV systems are calculated as follows:

$$Avoided\ GHG\ Emissions = Participation\ x\ Electricity\ Generated\ x \frac{1 + Losses}{1 + Rebound}\ x \frac{Grid\ Mix}{1000}$$

where,

Participation = program-caused PV installations
Electricity generated = lifetime electricity generation by PV system in kWh
Losses = % transmission losses
Rebound = % rebound effect
Grid mix = the total CO_2e emissions (kg/kWh) based on % energy mix of agency and emission factors for each energy source:

$$\sum \% \; Energy\ Sourece\ in\ Grid\ Mix\ x\ Emissions\ Factor\ for\ Energy\ Source$$

The emissions avoided are then translated into a monetary value by multiplying the amount of emissions avoided to the agency's value of carbon ($/ton CO_2e):

$$\$\ Benefit\ of\ avoided\ GHG\ emissions\ = avoided\ GHG\ emissionsvalue\ of\ carbon$$

2) Health improvement: health benefits are quantified with a dollar value based on the avoided cost of health detriment of criteria pollutants and the reduction of pollutant emissions across the lifetime of the PV system.

The reduction of pollutant emissions is calculated in the same way as the avoided GHG emissions above, where:

$$Avoided\ Criteria\ Pollutant\ Emissions = Participation\ x\ Electricity\ Generated\ x \frac{1 + Losses}{1 + Rebound}\ x \frac{Grid\ Mix}{1000}$$

The emissions avoided are then translated into a monetary value by multiplying the amount of emissions avoided to the avoided cost of health detriment caused by criteria pollutants. The toolkit provides 3 options (low, average, high) to the agency to determine how much they relatively value health impact in making their program selection and design decision. Based on their selection, a corresponding cost figure is used to calculate the monetary benefit of avoided criteria pollutant emissions.

$$\$\ Benefit = Avoided\ Criteria\ Pollutant\ Emissions\ x\ Cost\ of\ Health$$

Where cost of health is expressed in $/ton.

3) Revenue from interest and principal: the agency has the potential to gain revenue from the solar financing program depending on its interest rate and the number of people that participate. Total revenue includes both the loan principal and the resulting interest.

$$Total\ Revenue = Participation\ x\ (1 - Default\ Rate) x \sum Discuonted\ Loan\ Payments$$

where,

Default rate = expected % of participants who default on the loan
Discounted loan payment = monthly payment/(1 + agency discount rate)$^{month/12}$

The net revenue in the toolkit refers to the additional value that the agency gains by implementing the program, and is calculated by subtracting the principal from the total revenue:

$$Net\ Revenue = Total\ Revenue - (Average\ Loan\ Amount\ x\ Participation)$$

PV Model Emission Calculations

The calculation of the program's expected emission reductions considers the amount of electricity generated by program-caused solar PV systems to be the amount of energy sales avoided by the agency. Thus, the amount of emissions avoided is that which would have occured from generating the same amount of electricity plus a transmission loss factor, using the agency grid mix rather than by solar. Transmission loss accounts for the additional electricity generated by the agency that is lost during transmission and never reaches the customer.

The emissions reduction is determined using the equation:

$$Emissions\ Reduction = \frac{(Total\ Electricity\ Generated\ by\ PV)(PV\ Installation\ Caused\ by\ Program)(\ Agency\ Emissions\ Factor)}{1 + \%\ Rebound\ Effect}\ x\ (1 + \%\ Transmission\ Loss)$$

The agency emission factors for each GHG and pollutant are calculated by the equation summed across every energy source:

$$Emissions\ Factor = \sum Emissions\ Factor\ of\ Energy\ Source\ x\ \%\ Energy\ Source\ in\ Agency\ Energy\ Mix$$

Note that the emissions reduction calculation includes a rebound effect. This accounts for any increase in energy consumption after getting PV because a customer gets electricity from their PV system rather than from the agency. A small average rebound effect of about 2% has been observed among households that install PV systems (McAllister, 2012).

Results & Discussion

Summary of Solar PV Model Major Findings

- **Interest rates approaching the existing average rate cause few new PV purchases.** Program-caused PV purchases (and their associated GHG emission reductions) increase most rapidly a few percentage points lower than the existing rate, but level off at very low interest rates as the program budget is reached and PV financing is capped.
- **Agencies can use predicted program costs to choose a feasible interest rate.** Over a certain rate, revenue exceeds cost, but solar uptake is low.
- **The cost per ton of GHG emissions avoided is higher at low interest rates** when costs include program administrative costs, electricity sales lost due to PV, and the money lent out.
- **Health benefits alone are too small to justify offering incentives**, and can vary greatly depending on source electricity mix. Agencies with higher renewable content electricity mixes will see greater health benefits from PV rebates.
- **Agencies must consider societal benefits, cost-effectiveness, and default rates.** Higher interest rates minimize revenue losses or add revenue, while lower interest rates maximize health and GHG reduction benefits. Opening participation to people with low credit scores can increase PV uptake but also the risk of default and lost revenue.

The solar financing tool allows users to view the effects of different interest rates by manipulating the customer-owned interest rate while keeping other input values constant. To demonstrate model results, we ran the model under a range of interest rates and present sample model predictions below. We used input values including an average existing interest rate of 7.9 percent, a non-repayment rate of 5 percent, and a "medium" health impacts value. Other values were based on agency information from MCE Clean Energy and RCEA. We assumed 100 percent marketing effectiveness for ease of viewing results.

Effect of Interest Rate on PV Sales

Reducing the interest rate available for customer-owned PV through the CCE agency program results in an increase in solar PV uptake as shown in Figure 4. CCE agency electricity buyers are converted into PV buyers, while the market share of third party-owned PV stays constant (~0% change) at ~1.25% of market share. The total PV uptake is non-zero even at an interest rate equal to the existing average interest rate, as some people will switch to the CCE agency program due to their trust in the agency, ease of repayment, or simply having heard of the program before other financing products. The

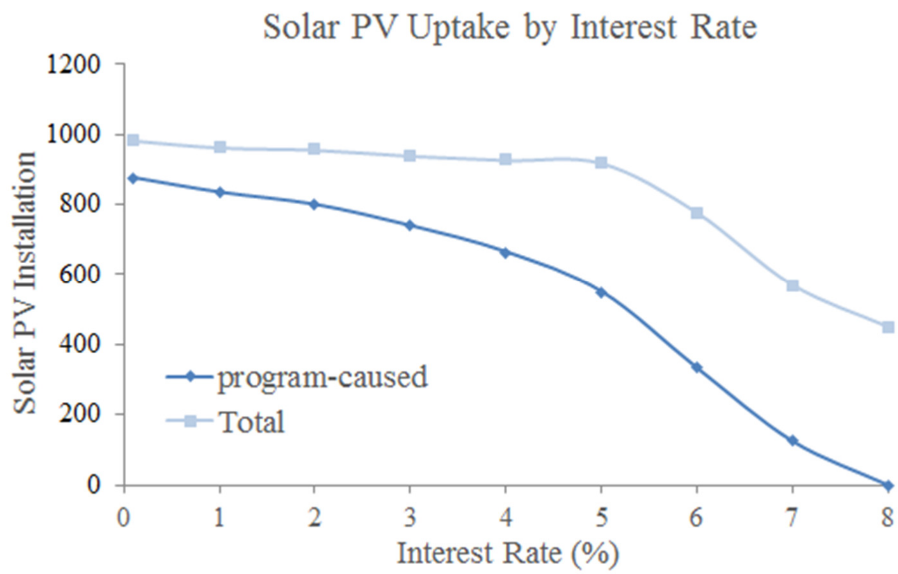
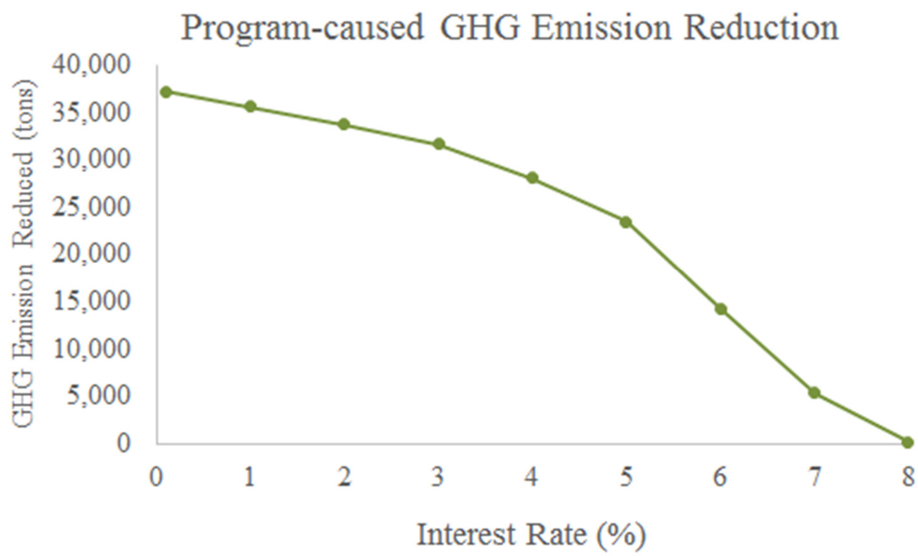


Figure 4. Estimated PV uptake caused by financing program with different interest rates.

Effect of Interest Rate on Greenhouse Gas Reductions

Figure 5 displays model predictions for program-caused GHG emission reductions and the cost of achieving those reductions depending on agency financing interest rate. The effect on GHG emissions decreases as interest rate increases, in direct relationship to the amount of solar uptake caused by each interest rate. The cost to reduce each ton of CO2e emissions is lowest at the interest rates closest to the area's existing interest rate. This is mainly because customers have to pay back more money to the agencies with higher interest rates, resulting in spending less money on this program or increasing agencies revenues. At an interest rate of 7 percent, the cost of GHG reduction is negative, meaning that agencies can increase revenue and reduce GHG emissions. Agencies can increase revenues with high interest rates, but only achieve small GHG emission reductions.



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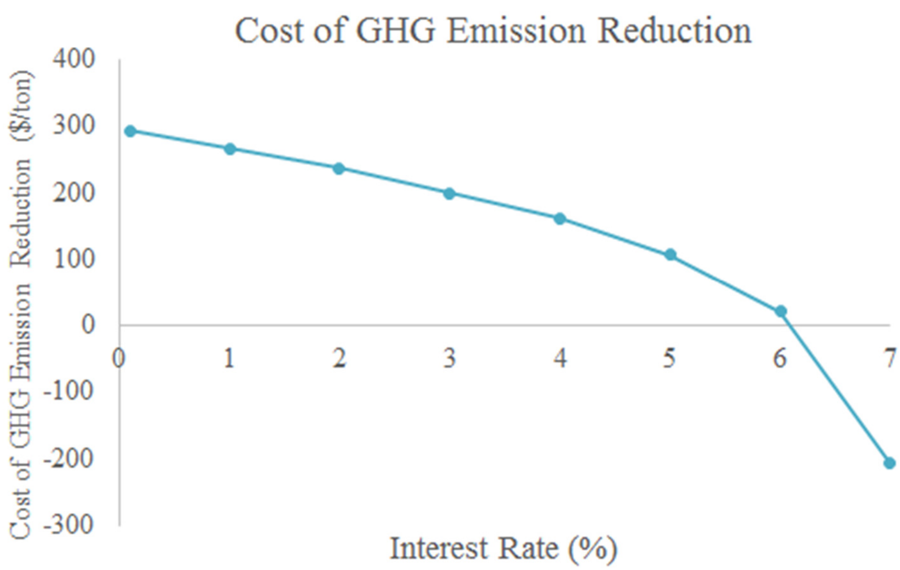

B

Figure 5. Effect of a range of interest rates from 0% to 7% on A) total predicted GHG emission reductions from the financing program, and B) cost of GHG emission reductions

Knowing the model outputs, customized for a particular geographic area, year, and predicted market penetration, a toolkit user can make an informed decision about how much money and effort to invest in a PV financing program.

Health Impacts of PV Interest Rates

The health benefits are the largest benefits at some interest rates and highly influence benefit-cost ratio. The absolute values of health benefits are even higher than that of revenue change at an interest rate between 5 and 6 percent. In addition, health impacts can vary depending on power plants' locations. If the fossil fuel-based power plants are located near the areas of high population density, the health impact should be "High", and indicate higher benefits than our analysis and vice versa.

Model usefulness

We chose the TCM to model solar uptake because consumer demand at each PV price point has fluctuated over the years due to external factors, making it difficult to construct an empirical demand function. For example, one time-dependent factor is that homeowners are pressured to install solar PV before rebates and tax credits expire. Another is unexpected policy forces; for example, PACE programs entering a community has led to an increase in solar uptake, while a 2010 Federal Housing Finance Agency decision halted most PACE financing (Gerdes, 2012; Kaatz & Anders, 2014; SCEIP Monthly, 2016). A third crucial factor is the amount of electricity charges credited back through NEM, which has decreased over time with the advent of the NEM 2.0 program design and migration to time-of-use rate schedules (Roselund, 2017).

Using a TCM enabled us to predict customer behavior using the parameters that determine customer decisions around PV, including the stochasticity of consumer behavior. Changes in many external factors can be adjusted as user inputs and the model re-calibrated to include them. The perceived cost of PV can also be used to smooth over some parameters. For example, we omitted to include a model element specifically for the federal Investment Tax Credit, which can provide a tax credit of up to 30% of the value of a PV system. But the perceived cost variable is set so that the predicted demand matches the observed demand anyway. However, the structure of the model itself will need to be edited if a whole new parameter is added. For example, this might be necessary if a significant portion of an agency's residential customers start to purchase its green electricity product, as some are already doing (McDermid, 2018), and alter their behavior by getting more or less PV than other customers. It might also be necessary if the California Public Utilities Commission alters NEM rules after its planned review of NEM 2.0 in 2019 (California Public, 2016).

Model limitations

We omitted the cost of replacing an inverter every ten years, which other analyses include (Simons, 2005). This is effectively incorporated somewhat as part of the perceived cost of PV, but a more detailed analysis might include an average or a range of inverter costs in the cost of PV. As mentioned in the previous section, we omitted the Investor Tax Credit from our analysis. We also omitted the fact that some homeowners deduct PV financing interest and possibly even principal from their property taxes (Feldman & Bolinger, 2016).

Sensitivity Analysis

This model's predictions depend on the difference between on user-input existing and CCE agency interest rates. The average existing interest rate available in an area may be difficult to find out or estimate with any certainty, because it may vary by location and the creditworthiness of the population. This fact can lead to user uncertainty over the dependability of results. The model's default rate is an average over a wide geographic range as found on relevant financing websites.

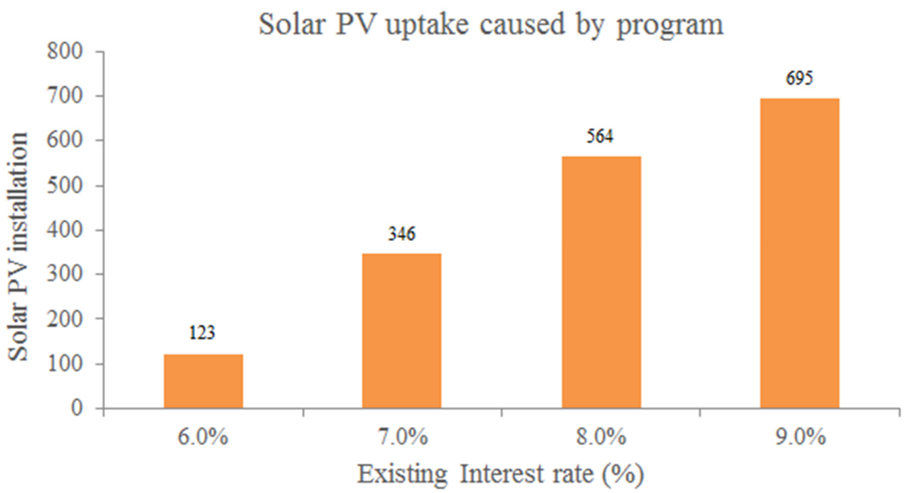

Figure 6. Change in solar uptake with different existing (non-CCE) interest rates when the CCE agency financing interest rate is 5 percent.

Finally, the standard deviation of the perceived cost was chosen arbitrarily, as we found no data on how much perceived costs vary among consumers. A sensitivity analysis using the same sample parameters as the examples above shows that, depending on the agency's financing interest rate, a low standard deviation of 10% can increase solar uptake by about 400% relative to a standard deviation of 30%. The cost per ton of GHG emissions avoided is less variable except at agency financing interest rates near 7%. At 7% interest rate, an agency can achieve an overall positive net revenue from each solar loan provided after accounting for program costs and administrative expenses, which means total costs are negative. Also, a low standard deviation in the perceived costs (10%) causes higher solar uptake than higher standard deviations (30%) of those perceived costs. As a result, the low standard deviation results in greater GHG emission reductions. Since the cost of GHG reduction is total costs divided by total GHG reduction, being inversely proportional to GHG reduction, the greater GHG emissions result in negative and lower cost of GHG reduction with the low standard deviation at 7% interest rate.

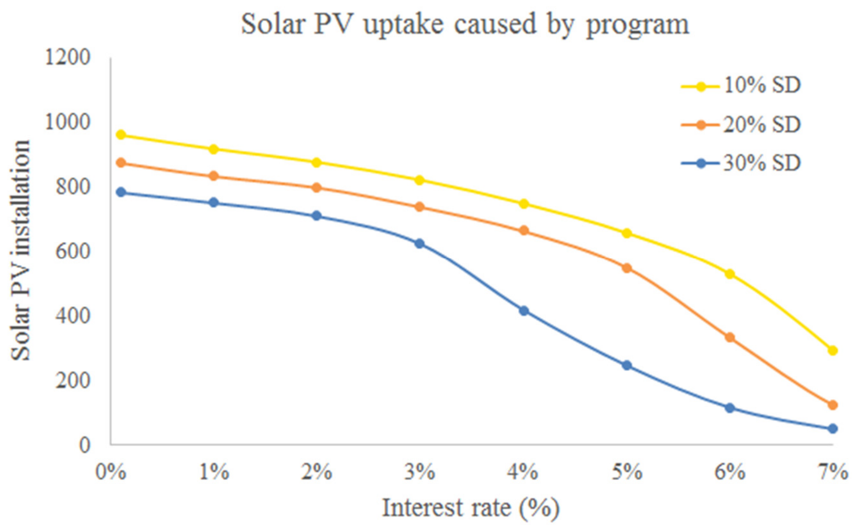

Figure 7. Change in solar uptake with different noise scenarios. In low noise scenario, standard deviation is 10 percent of mean values. For the standard deviations in medium and high noise scenarios, 20 percent and 30 percent of mean values are used, respectively.

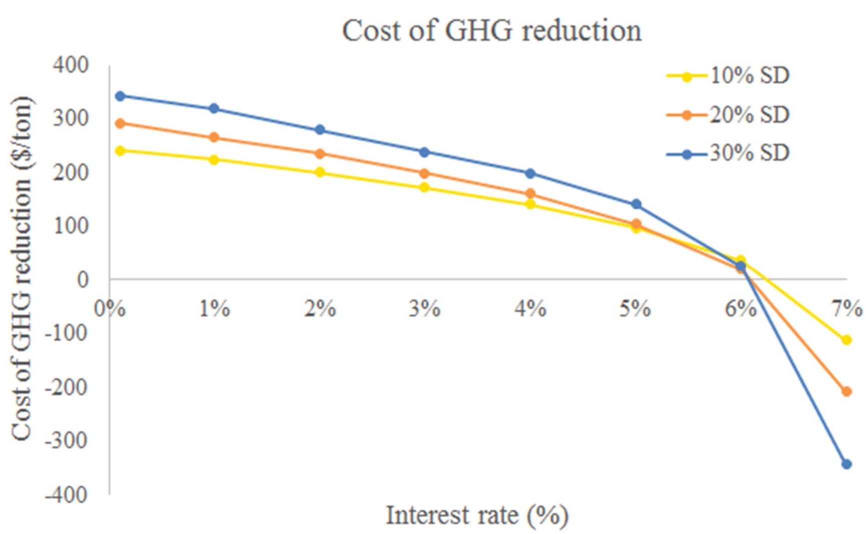

Figure 8. Change in cost of GHG reduction with different noise scenarios. In low noise scenario, standard deviation is 10 percent of mean values. For the standard deviations in medium and high noise scenarios, 20 percent and 30 percent of mean values are used, respectively.

Indoor Fuel Switching Program

Background and Overview

The largest contributors of GHG emissions in California are transportation and electricity generation. CCE agencies already procure low-GHG electricity and our EV model will help agencies reduce GHG emissions from the transportation sector. CCE agencies have limited influence over industrial operations and agriculture; therefore, indoor fossil fuel combustion is the last major GHG emission source that CCE agencies can manage at scale. We analyzed one possibility of fuel switching in the residential sector as a starting point for agencies.

The importance and benefits of fuel switching

Fossil fuel combustion within the home represents a significant source of GHG emissions. In 2016, 64.6% of California housing units relied on natural gas for heating (U.S. Census Bureau, 2017). In 2009 the average California household used 22 thousand cubic feet of natural gas per year for space heating and 16 thousand cubic feet of natural gas for water heating, resulting in 2 metric tons of GHG emissions per home per year (2009 RECS, 2013). These two uses account for 95% of a household's total natural gas usage. Homes may use additional natural gas fired devices like stoves and clothes dryers, but our report will focus mainly on household heating requirements.

Heat pumps use electricity to power a system of compressors, pumps, and refrigerants to move heat either into or out of a building, similar to how refrigerators work. Heat pumps are highly efficient and typically have Coefficients of Performance (COP) as high as 3 or 4, meaning they move up to 4 units of heat for every unit of electricity they use. The efficiency is effectively greater than 100%. A natural gas furnace cannot extract more heat energy than what is contained in the fuel, limiting its total efficiency to 100%. CCE agencies typically have a high percentage of renewable electricity, minimizing the GHG impact of additional electricity consumption.

Increasing heat pump adoption is included in many government GHG reduction strategies. In Europe, heat pumps can avoid 230 million tons of GHGs by 2020, 20% of Europe's CO_2 emissions target (Bayer et al., 2012). Thirty-two percent of New York's energy-related GHG emissions are from residential and commercial heating and heat pumps could potentially meet 70% of the state's heating and cooling loads (NYSERDA, 2017). Throughout the Northeast and Mid-Atlantic regions heat pumps could avoid 7 million metric tons of GHG emissions per year (NEEP, 2014).

Barriers to fuel switching

There are several reasons there has not been a mass uptake of heat pump technology. Multiple heating options exist, including natural gas furnaces, air-source heat pumps, ground source heat pumps, solar thermal water heating, and biomass heating systems. Each has its own advantages and disadvantages and it may be overwhelming for homeowners to decide on a specific technology. High upfront cost has been a major barrier for residents to install heat pumps or other renewable heating technologies (Caird & Roy, 2010; NYSERDA, 2017; NEEP, 2014). For example, it costs an average of $6,000 to purchase and install a heat pump in California, but may be as high as $10,000 depending on brand, home size, and other factors (Home Advisor, 2018). Natural gas furnaces; however, only cost $4500 on average in California (Home Advisor, 2018). Heat pump performance can be an issue because they are less effective at lower ambient air temperatures, causing user complaints in severe winter conditions and potentially requiring a secondary heating system (Singh et al., 2010). California has mild winters and current technologies are can provide sufficient heating at ambient temperatures as low as zero degrees Fahrenheit; therefore, minimal performance issues are expected in the state. Another potential challenge is the frequency that homeowners consider purchasing new heating systems. Our discussion with one of MCE's representatives revealed that homeowners usually replace major appliances when the old one fails resulting in a short time frame to educate potential buyers on heat pumps.

Low natural gas prices and high electricity prices may reduce the cost-effectiveness of switching away from natural gas based heating systems. In 2016, Californians paid 3.9 cents for a kWh equivalent quantity of natural gas, while residential electricity rates were 17.4 cents per kWh (EIA, 2017). New Energy Star natural gas furnaces must be at least 90% efficient, and some models are 97% efficient (Energy Star, n.d.). Given this, heat pumps must be approximately 4.5 times more efficient than a natural gas system to have lower operating costs. Air-source heat pumps with a COP of 4 can match the operating costs of a typical 90% efficient furnace given California's energy prices. Additionally, modern air-source heat pumps are reversible so they can provide cooling during the summer. This can save on cooling costs and provide comfortable indoor temperatures all year long. Combining a heat pump with rooftop solar can lower a household's electricity costs to further reduce a heat pump's operating costs.

Potential Methods for Overcoming Barriers

There are methods for overcoming these barriers. A UK study found that people adopted microgeneration heating technologies including solar thermal hot water, heat pumps, biomass stoves, and micro combined heat and power because they wanted to reduce their carbon footprints and save money on their fuel bills and ultimately decided on a technology that had a higher perceived reliability and faster paybacks (Caird & Roy, 2010). Note that natural gas is almost twice as expensive in the UK as in the United States, so UK homeowners are more likely to realize cost savings by switching from natural gas to electricity (British Petroleum, 2017). Regional climatic conditions influence the attractiveness of heat pumps. Western European countries like Italy, France, and Spain that have lower heating and cooling demands witnessed a much higher heat pump adoption rate than the UK (Singh et al., 2010). Given California's similar climate, heating, and cooling needs, heat pumps are an attractive option. Even in less favorable climates, heat pumps can prove cost effective if the existing heating source is expensive such as fuel oil or electrical resistance heaters. Homes in the northeastern United States that displace or fully replace their fuel oil heating systems with heat pumps can save between $327 and $948 per year (NEEP, 2014). Homes that replaced electric resistance with heat pumps saved an average of 3,000 kWh per year, equal to $459 (NEEP, 2014). California does not have many fuel oil heating systems, but it does have electrical resistance heating systems. Targeting homes that have electric resistance heating systems are more likely to provide homeowners with cost savings and start increasing awareness of heat pumps.

There are some financial incentives for HVAC upgrades but are typically included as eligible options for general home energy improvement incentives. Up to $500 in federal tax credits for energy improvements including heating and cooling upgrades were available up through 2016, but have since expired (USEPA & USDOE, n.d.). Energy Upgrade California provides rebates up to $5,500 for comprehensive home energy upgrades including better insulation, duct sealing, and HVAC replacements (Southern California Edison, n.d). In 2017, Marin Clean Energy launched a pilot program offering up to $1,200 for low-income family and tenants to install a variety of energy efficient devices including heat pumps (Marin Clean Energy, n.d.).

Changing regulations may make heat pumps more favorable than natural gas based systems. California's Energy Efficiency Strategic Plan calls for all new single and multi family homes to be zero net energy (ZNE) by 2020 and new commercial buildings to be ZNE by 2030 (California Public, 2008). This would require new buildings to consume no more energy than they generate on site over a year. Meeting this goal combines minimizing total energy use and increasing distributed energy resources. Given that heat pumps use less energy than natural gas furnaces, homes with heat pumps would need to generate less energy onsite. California's implementation plan for meeting these ZNE requirements includes improving the thermal integrity of buildings by incorporating radiant cooling, ductless systems, and heat pumps into at least 50% of new construction by 2020 (California Public, 2008).

Methods

We developed a model that calculates the environmental benefits of replacing a home's natural gas furnace with an air-source heat pump. Results can also be interpreted as the avoided emissions if a new residence is built with a heat pump instead of a natural gas furnace.

Annual Energy Usage for Space Heating

We used the average energy usage for natural gas fired central air furnaces and electrically powered heat pumps from the 2009 Residential Energy Consumption survey (RECS), the most recent data available. This data set estimates the actual energy usage used in 2009 for specific purposes in each region of the United States. Based on the 2009 RECS data 60% of California homes with heat pumps did not use a secondary heating source. Given California's low winter heating requirements and that modern low temperature heat pumps have internal electric resistance heaters to provide supplemental heating when necessary, we assumed that newly installed air source heat pumps do not require a secondary heating device (Johnson, 2013). Residences may choose to leave in existing heating systems when they install heat pumps but for the above reasons, we assumed that these will have zero to negligible use.

Emission Reduction

Emissions for natural gas combustion in furnaces are referenced from USEPA AP-42 emission factors, except for NOx. California has specific NOx emission factors for residential natural gas furnaces. South Coast Air Quality Management District (SCAQMD) and San Joaquin Air Valley Air Pollution Control District reduced the NOx emission standard for new natural gas furnaces from 40ng/J to 14ng/J in 2014. In January 2018 some manufacturers including Lennox and Rheem have developed models that meet the lower limit (Lennox, 2018; Rheem, 2018). While the 40ng/J limit was implemented at different times for different agencies, both SCAQMD and Bay Area AQMD, covering some of the most populous areas of the state, implemented this limit in 1983. Due to the large market in both of these areas it is reasonable to assume that manufacturers did not make multiple models with different NOx limits and sold a 40ng/J limit furnace throughout the entire state. As a result, we assume that the majority of existing furnaces replaced by heat pumps meet the 40ng/J limit. Emissions from electricity generation are calculated using the same methods as in the EV model. We calculated the changes in emissions using a 15 year lifetime of modern heat pumps (USDOE, n.d.). Net emission changes are calculated using the same methods as the EV model.

Results and Discussion

Summary of Heat Pump Model Major Findings

- **Heat pumps are effective at reducing CO_2 emissions.** Depending on the energy mix, one heat pump can prevent between 0.64 tons and 1.25 tons of CO_2e emissions per year.
- **California has an ideal climate for heat pumps.** Relatively mild winters means that heat pumps can efficiently provide indoor space heating without a secondary heating source.
- **Low natural gas prices and high electricity prices** make it difficult for homeowners to realize cost savings by using a heat pump for heating needs. Combining heat pumps with solar panels may reduce the operational cost so homeowners can realize cost savings.
- **Criteria pollutant emissions may increase by using heat pumps.** Depending on the energy mix, emissions of NOx, SOx, and PM may increase, albeit by typically less than one pound per year, by using heat pumps. These tradeoffs must be considered when installing heat pumps.

The heat pump model calculates the net emission reduction from switching one natural gas furnace to an air source heat pump over the 15 year lifetime of the device. Emission reductions vary based on the agency's respective energy mix; however, GHG emissions decrease substantially for all agencies based on their 2016 power mix (Table 6). Power content labels for 2017 had not been released at the time of this report, so we were unable to analyze the emissions reductions of some of the newer CCE agencies. Residential natural gas furnaces in California have very stringent NOx emission limits compared to utility-scale power plants. As a result, there is an increase in NOx emissions, represented by negative reductions in Table 6, by using heat pumps if an agency includes natural gas or biomass in their energy mix. SOx emissions tend to increase with heat pump use as the quantity of biomass or geothermal energy used in the agency mix increases, as both of these sources have greater SOx emission factors than natural gas. PM emissions will increase by using heat pumps if there is biomass in the agency energy mix.

Table 6. Emission Reductions by Replacing a Natural Gas Furnace with a Heat Pump

Agency	GHG (tons/ device)	NOx (pounds/ device)	SOx (pounds/ device)	PM2.5 (pounds/ device)	VOC (pounds/ device)
Sonoma Clean Power	18.93	-2.49	-0.68	2.46	1.73
Clean Power SF	17.39	-5.49	0.10	2.28	1.55
Lancaster Choice Energy	9.59	-27.63	-8.01	-35.25	-0.83
Peninsula Clean Energy	14.78	-10.47	0.01	2.00	1.25
Marin Clean Energy	15.50	-11.02	-1.92	-7.10	0.95

The net environmental and health benefits of installing heat pumps are generally positive; however, net benefits are negative when biomass is part of the energy mix, due to the relatively high health impact from PM emissions (Table 7). The benefits assume the mean health impact values, 5% discount rate, and market price of carbon as done with the other models.

Table 7. Net Benefits by Replacing a Natural Gas Furnace with a Heat Pump

Agency	GHG ($/ device)	NOx ($/ device)	SOx ($/ device)	PM2.5 ($/ device)	VOC ($/ device)	Total
Sonoma Clean Power	$170	$-20	$-10	$302	$4	$447
Clean Power SF	$156	$-43	$2	$281	$4	$399
Lancaster Choice Energy	$86	$-217	$-119	$-4,331	$-2	$-4,583
Peninsula Clean Energy	$133	$-82	$0	$246	$3	$300
Marin Clean Energy	$139	$-87	$-29	$-872	$2	$-846

Increasing heat pump adoption can significantly reduce greenhouse gas emissions, with most agencies reducing GHG emissions by more than 1 ton per year per device. There is a tradeoff that there may be increases in some criteria pollutants depending on the agency's energy mix. As with the EV program, agencies should green their electricity as much as possible to maximize the benefits of electrically based heating systems. Our model is limited by using average national emission factors for different generation sources and may not reflect the actual emissions from an agency's power source. Since we did not complete a full TCM model, we are unable to determine the quantity of heat pumps that would be purchased under a given financial incentive and the resulting cost effectiveness of the program. Agencies can estimate their cost of GHG reduction from heat pumps by dividing the expected GHG savings from a heat pump by any financial incentives they provide and their expected labor costs to run the program.

Given the relatively low cost of natural gas based heating systems, it may prove difficult to convince homeowners to switch without significant financial incentives and education. Agencies should target homes that use other electric heating sources like electric resistance heating systems and portable electric heaters because heat pumps can result in significant cost savings compared to those technologies. Homes with rooftop solar are also good candidates since they experience a lower electricity cost. Agencies can work with developers to design new or retrofitted housing units with heat pumps instead of natural gas furnaces meet California's ZNE goals. Lastly, agencies should target environmentally conscious ratepayers to increase heat pump usage since they may have a greater willingness to pay for environmental benefits.

Comparative Cost-Effectiveness

Agency staff members can use this toolkit to compare the cost-effectiveness of different implementation strategies among a few different program types, allowing them to see what combinations of measures will help them achieve their missions to the greatest degree considering their budgets.

CCE agencies should consider all possible options to reduce GHG emissions and select the most cost-effective options first. Agencies, for example, could reduce the GHG intensity of their electricity mix instead of giving financial incentives to EVs, solar panels, or electric appliances. We can compare the cost-effectiveness of our programs to the cost of replacing GHG emitting energy sources with additional solar, wind or small hydro power. We defined our "breakeven price" as the maximum additional cost of procuring GHG-free electricity ($/MWh) relative to a GHG emitting source to have the same cost-effectiveness as the program (Table 8).

$$Breakeven\ price\ = (Program\ effectiveness)(GHG\ intensity)$$

where,

$Program\ effectiveness\ =\ dollars\ spent\ on\ program\ to\ remove\ one\ ton\ of\ GHG\ emissions\ (\$/ton)$

$GHG\ intensity\ =\ GHG\ emissions\ from\ one\ MWh\ of\ electricity\ from\ a\ particular\ source\ (ton/MWh)$

If an agency is solely looking to find the most cost-effective way to reduce carbon and it can procure renewable GHG-free electricity for less than the breakeven price of a given program, the agency should green its electricity first. If the added cost of GHG free electricity is more than the price listed in Table 8 at a given program GHG reduction cost, then the GHG reduction program is the more cost-effective choice. For example, if a modelled program results in a GHG reduction cost of $125/ton, and it costs an agency more than $57.73/MWh to switch from natural gas to solar, wind, or small hydro, the program is the more cost effective choice. If the cost of switching from natural gas to renewable GHG-free electricity is less than $57.73/MWh, procuring GHG free electricity is more cost effective than the aforementioned program. In the same scenario, if the agency wanted to replace biomass electricity instead of running the program, the added cost to replace biomass electricity with GHG free renewable energy would need to be less than $51.26/MWh to be cost effective. If agencies can procure GHG free electricity for less than the cost of procuring natural gas, the agency would experience both a cost savings and GHG reduction; outperforming our modeled energy programs. Understandably, agencies may not be able to immediately remove GHG emitting sources due to existing purchase contracts and the time needed to develop additional renewable resources. The agency must consider the relative time frames it would take to implement energy programs and change their energy mix.

Table 8. Maximum Added Cost of GHG-Free Electricity ($/MWh) to Offset Different Energy Sources to Match Cost Effectiveness of Energy Programs

Program GHG Reduction Cost ($/ton-$CO_2$e)	**Natural Gas**	**Biomass**
$50	$23.09	$20.50
$75	$34.64	$30.75
$100	$46.19	$41.01
$125	$57.73	$51.26
$150	$69.28	$61.51
$175	$80.83	$71.76
$200	$92.37	$82.01

Table 9 shows the range of levelized costs of energy (LCOEs) in $/MWh for renewable energy sources coming online in 2019 with and without tax credits. This would not reflect the price an agency would pay for the electricity because the producer would apply a reasonable markup, but it provides a useful comparison. With tax credits, renewable electricity would reasonably cost an agency between $35-$65 per MWh. This ignores the added cost of energy storage that is becoming increasingly important with renewable energy deployment. Natural gas would reasonably cost an agency between $50-60$ per MWh, in the same range as renewable energy. Because the cost difference between natural gas and renewable energy is expected to be small, it appears that agencies may more cost effectively reduce GHG emissions by greening their mix before offering incentives to EVs or rooftop solar PV panels.

Table 9. LCOE of Energy Coming Online in the US in 2019 ($/MWh)

Technology	LCOE Without Tax Credits			LCOE With Tax Credits		
	Low	Average	High	Low	Average	High
Wind-Onshore	$40.40	$52.4	$69.40	$22.6	$34.50	$51.60
Solar PV	$53.50	$70.10	$129.90	$41.30	$53.10	$96.40
Hydroelectric*	$57.40	$63.90	$69.80	$57.40	$63.90	$69.80
Wind-Offshore*	$136.60	$157.40	$212.90	$125.10	$145.90	$201.40
NG Conventional Combined Cycle	$45.80	$49.30	$58.90	N/A	N/A	N/A
NG Advanced Combined Cycle	$45.10	$45.20	$56.20	N/A	N/A	N/A

*Values for hydroelectric and wind-offshore are for systems coming online in 2022.
Source: US Energy Information Administration

An agency could consider buying offsets, and while some offsets may be very cheap they are unlikely to directly benefit the CCE agency's community. Many CCE agency missions involve creating clean, sustainable communities. As a result, it is unlikely that an agency would fund projects outside of its community.

Successful Practices Guide

In addition to building our models, we composed a Successful Practices Guide for CCE agencies to use when designing and implementing programs. The guide provides recommendations and lessons learned regarding aspects of program design that are not captured in our models. Agencies can use our models and guide together to maximize the effectiveness of their programs.

We first conducted interviews with CCE agency staff members and other experts to compile a set of programs of interest and to learn from their first-person knowledge of these programs. We focused on programs to encourage EV, PV, and indoor fuel switching. We then collected relevant information on programs conducted by as many CCE agencies and other organizations (e.g. local governments) as possible in order to avoid selection bias, through interviews, program-related documents, and academic literature. After collecting all the practices and results possible, we examined each practice and determined which factors led to the success or failure of each program. We also defined possible problems that might occur and explore possible solutions as well as methods to maximize net benefits. Finally,
when documenting successful practices, we included any case-specific conditions affecting each practice we found.

Conclusion

CCE agencies are looking for ways to design and implement the most impactful energy programs possible in their communities. Many agencies are new and lack robust program decision making frameworks, have difficulty predicting the public response, and are unsure of the the resulting costs and benefits of the energy programs.

We identified three energy programs that CCE agencies might implement: EV incentives, residential solar PV financing, and heat pumps. We developed TCMs for incentivising EVs and financing residential solar PV, which capture monetary and non-monetary values to predict how consumers may respond to economic incentives for green technologies. Our models calculate the resulting monetary, environmental, and health benefits of these programs. For indoor heat pumps, we developed a simpler model that calculates the environmental and health benefits of switching from natural gas-based to electricity-based heating. We then developed an interactive toolkit based on these models so agencies can visualize the potential effects of these programs with different design parameters.

Given the financial and environmental focuses of many CCE agencies, we believe that the toolkit outputs related to program financial viability and cost of GHG emission reductions will be particularly useful to them. The toolkit can help agencies determine the EV and PV programs' financial viability and GHG emission reduction costs at different incentive levels or interest rates. Once an agency has determined the optimal program designs for its circumstances, it can consult our successful practices guide for strategies to improve program execution and maximize program benefits.

Generally, each of the modeled programs results in net GHG emission reductions, but increasing electricity consumption from EVs and heat pumps may result in increases in criteria pollutants depending on the energy mix. Agencies must consider these trade-offs as they work to electrify their communities. CCE agencies should continue to green their electricity mixes to maximize the environmental and health benefits of these programs.

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Appendices

Appendix A. 100-year Global Warming Potential (GWP) from IPCC (2014)

GHG	GWP
CO_2	1
CH_4	28
N_2O	265

Appendix B. Emission factors from electricity generation

Fuel Type	CO2e (kg/kWh)	NOx (kg/kWh)	SOx (kg/kWh)	PM (kg/kWh)
Coal	1.004	2.53×10^{-3}	6.64×10^{-3}	1.43×10^{-3}
Natural Gas	0.419	3.80×10^{-4}	7.13×10^{-6}	2.17×10^{-5}
Biomass	0.372	9.27×10^{-4}	6.03×10^{-4}	2.81×10^{-3}
Geothermal	0.026	0	1.59×10^{-4}	0
Large Hydro	0.011	0	0	0
Nuclear	0	0	0	0
Solar, Wind, Small Hydro	0	0	0	0
Unspecified Sources	0.419	3.80×10^{-4}	7.13×10^{-6}	2.17×10^{-5}

Appendix C. Vehicles included in the EV model, organized by engine type and vehicle class.

Engine Type	Vehicle Class	Included Models
Internal Combustion Engine	**Subcompact**	Nissan Versa, Kia Soul, Honda Fit, Hyundai Accent, Fiat 500
	Compact	Honda Civic, Toyota Corolla, Chevrolet Cruze, Nissan Sentra, Hyundai Elantra
	Midsize	Honda Accord, Toyota Camry, Nissan Altima, Ford Fusion, Hyundai Sonata
	Large	Dodge Charger, Toyota Avalon, Chevrolet Impala, Nissan Maxima, Chrysler 300
	Near & Entry Luxury	Mercedes-Benz C-Class, BMW 3-Series, Lexus IS, Lexus ES, BMW 4 series
	Luxury and High End Sports	Mercedes-Benz E-Class & CLS-Class, BMW 5-Series, Mercedes-Benz S-Class, Lexus GS
	Sports	Ford Mustang , Chevrolet Camaro, Dodge Challenger, Hyundai Veloster, Marzda-MX5
	Compact & Subcompact SUV	Toyota RAV4, Honda CR-V, Nissan Rogue, Subaru Forester, Mazda CX-5
	Mid & Large SUV	Ford Explorer, Toyota Highlander, Subaru Outback, Jeep Grand Cherokee, Honda Pilot
	Luxury Subcompact & Compact SUV	Lexus NX, Mercedes GLC/GLK-Class, Audi Q5, Acura RDX, BMW X3
	Luxury Mid & Large SUV	Lexus RX, Mercedes GLE/M-Class, BMW X5, Acura MDX, Mercedes GLS/GL Class
Non-Plugin Hybrid	**Subcompact**	Toyota Prius C
	Compact	Ford C-Max hybrid, Toyota Prius, Toyota Prius V
	Midsize	Ford Fusion Hybrid, Honda Accord Hybrid, Toyota Camry Hybrid, Hyundai Sonota Hybrid, Chevrolet Malibu Hybrid
	Large	Toyota Avalon Hybrid
	Luxury Hybrid Non Plug in	Lexus CT200h Hybrid, Lincoln MKZ Hybrid, Lexus ES Hybrid
	Compact SUV	Toyota RAV4 Hybrid
	Midsize SUV	Toyota Highlander Hybrid
	Luxury SUV	Lexus NX Hybrid, Lexus RX 400 / 450 Hybrid
Plugin Hybrid	**Compact**	Chevrolet Volt, Ford c-Max Energi
	Midsize	Toyota Prius Prime, Ford Fusion Energi, Hyundai Sonata Hybrid
	Sports	BMW i8
	Luxury	Audi A3 e-tron, BMW 330e
	Luxury High End	Mercedes S550e Plug In
	Luxury Midsize	BMW X5 eDrive, Porsche Cayenne Hybrid, Volvo XC90 Hybrid
Battery Electric	**Subcompact**	Fiat 500e, Chevrolet Spark EV, Smart Fortwo, Kia Soul EV
	Compact	Chevrolet Bolt Nissan Leaf, Volkswangen e-golf, Ford Focus Electric
	Luxury	BMW i3 (Luxury), Mercedes B-class EV
	Luxury High End	Tesla S
	Luxury SUV	Tesla X

Appendix D. Car models missing cost data and their sources for substitute data

Segment	Model	Used data from
Sport Plug-in Hybrid	BMW i8	Volvo XC90 Hybrid
Luxury SUV Plug-in Hybrid	BMW X5 eDrive	Volvo XC90 Hybrid
Subcompact EV	Smart Fortwo EV	Chevrolet Spark EV
Subcompact EV	Kia Soul EV	Chevrolet Spark EV
Compact EV	Volkswagen e-golf	Nissan Leaf
Compact EV	Chevrolet Bolt	Chevrolet Bolt
Luxury Small EV	Mercedes B-class EV	BMW i3
Luxury High End EV	Tesla S	BMW i3 & Porsche Cayenne Hybrid
Luxury SUV EV	Tesla X	BMW i3 & Porsche Cayenne Hybrid

Appendix E. Criteria used to filter the NEM California Distributed dataset (2017) to give number of houses with existing PV systems in 2015. Only data that matched the Included Values for each Category were included in the housing count.

Category Name	Included Values
Application Status	Interconnected
Technology Type	Solar PV
Customer Sector	Residential
Project is VNEM, NEM-V, NEM-AGG?	No