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Participation Gap Analysis Among Energy Efficiency Programs in California's Public Sector — DRAFT Report

Prepared by the Clean Energy Transformation Lab (CETLab), University of California Santa Barbara (UCSB) on behalf of the California Energy Efficiency Coordinating Committee (CAEECC) Underserved Working Group

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Abstract

Energy efficiency programs funded by investor-owned utilities have become increasingly prevalent in the state of California as we move closer towards our climate and energy goals. Although these programs are available to all eligible entities, participation and investments are likely not equitable across regions and socio-economic factors.

In this research study, led by the Clean Energy Transformation Lab (CETlab) at the University of California Santa Barbara, in collaboration with California Energy Efficiency Coordinating Committee (CAEECC), we investigate potential gaps in participation, investments, and energy savings in energy efficiency programs aimed at public sector entities, specifically local governments and K-12 public schools.

We use Welch's t-tests to investigate differences between programs with the highest and lowest investments and savings. We also employ multivariate regressions to understand the relationship of investment and energy savings with various explanatory variables. Finally, we spatial map our data to visualize patterns of program participation and socio-demographic data.

Our results show that the degree of rurality is a significant factor that determines participation, investments, and energy savings in local government energy efficiency programs. More rural counties are less likely to participate and those that do participate have lower investments and energy savings compared to more urban counties. At the city-level, utility support through on-bill financing and non-resource programs contribute to the drivers of investment and energy savings in local government programs. For K-12 public school programs, the percentage of eligible students for a free and reduced meal plan and the percentage of Title 1 schools explain differences in investment and savings.

This research looks at participation data only from the years 2017 to 2019. Historical data on participation prior to 2017 would improve this analysis. Further, surveys and interviews of participants and stakeholders, especially in underserved areas, would be critical to fully understand the barriers to participation. Such evaluation is essential to ensure equitable access to energy efficiency programs across the state of California.

I. Introduction

This research study, led by the Clean Energy Transformation Lab (CETlab) at the University of California Santa Barbara, in collaboration with California Energy Efficiency Coordinating Committee (CAEECC), investigates potential gaps in participation in energy efficiency programs aimed at public sector entities in California.

A. Research Questions

The purpose of this research is to identify gaps in participation of energy efficiency programs in the public sector. More specifically, we ask the following research questions:

1. Are there gaps in program participation by geographic areas?
2. Are there gaps in program participation by public agency criteria?
3. Are there gaps in program participation by socio-demographic groups?

Within each research question, we analyze three indicators: participation, investment, and energy savings. Table 1 lists the various research questions, indicators, and measurements that we analyze in this project.

Table 1. Overview of research questions, indicators, and measurements to identify underserved participants in the public sector

Research Question	Indicator	Measurement	Data Sources
Are there gaps in program participation by geographic areas?	Participation	Number of public agencies participating by county and by city	CEDARS, Census
	Investment	Dollars (incentives)	CEDARS, Census
	Energy Savings	kWh or therms saved per public agency	CEDARS, Census
Are there gaps in program participation by public agency criteria?	Participation	Number of public agencies participating by type of public agency (local government and K-12)	CEDARS
	Investment	Dollars (incentives)	CEDARS
	Energy Savings	kWh or therms saved per public agency	CEDARS

Are there gaps in program participation by socio-demographic groups?	Participation	Number of public agencies by county and city income level, tax revenue, and calculated DAC proportion (pollution burden and population characteristics)	CEDARS, Census Tract, CalEnviroScreen
	Investment	Dollars (incentives)	CEDARS
	Energy Savings	kWh or therms saved per public agency	CEDARS

CEDARS: California Energy Data and Reporting System

II. Methodology

This research focused on two main groups of energy efficiency programs: local government programs analyzed at the county-level and city-level and K-12 public school programs analyzed at the county-level.

Public sector energy efficiency programs can be classified into four main categories as shown in Table 2. Among these categories, the local government category has the largest number of programs, gross measure costs, and lifetime kWh savings (Figure 1, 2, 3). In this analysis, we focus only on the local government energy efficiency programs because of the large data set provided through CEDARS. Data on energy efficiency programs within other public agency categories (state, federal, education) have low sample sizes and do not provide adequate heterogeneity for a robust statistical analysis. Further, some of the public sector entities such as the University of California (UC)/ California State University (CSU) Partnership and Department of Correctional Facilities are centrally managed and their participation is likely not correlated to the characteristics of the geographic area where they are located. In addition to the local government programs, we also evaluate energy efficiency program participation by K-12 public schools in California.

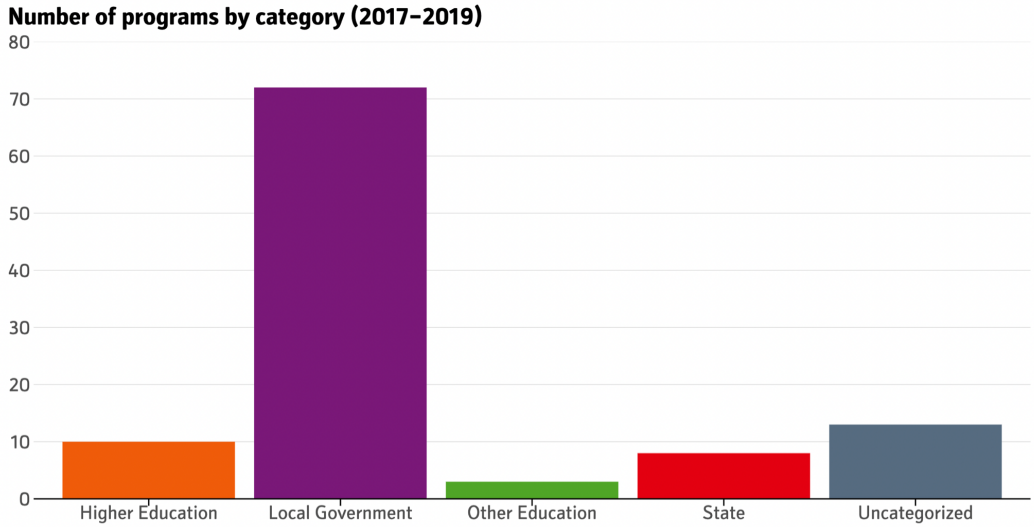

Figure 1. Number of programs by category between 2017 and 2019. Federal programs are state partnerships and are included in the state category. K-12 programs are included in the "Other Education" category. Source: CEDARS.

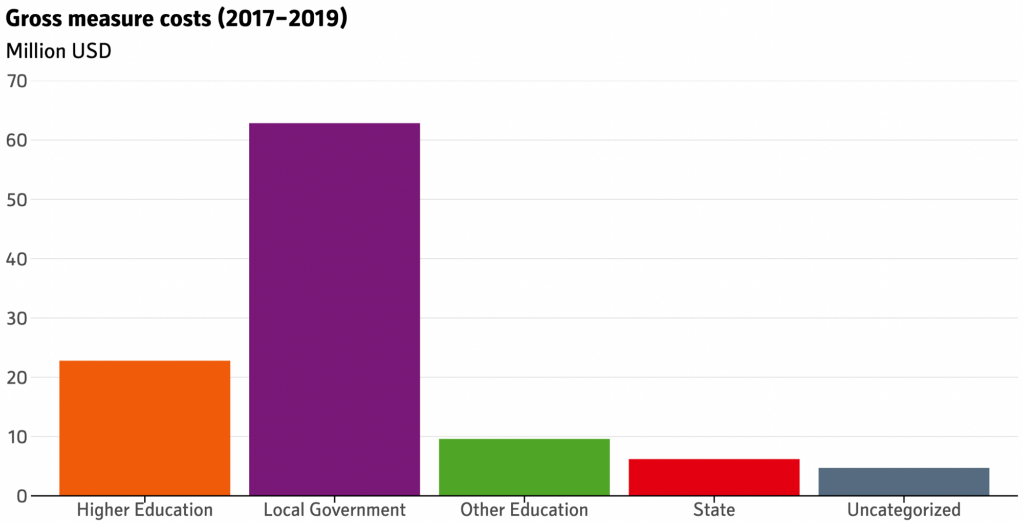

Figure 2. Total gross measure costs by category between 2017 and 2019. Federal programs are state partnerships and are included in the state category. K-12 programs are included in the "Other Education" category. Source: CEDARS.

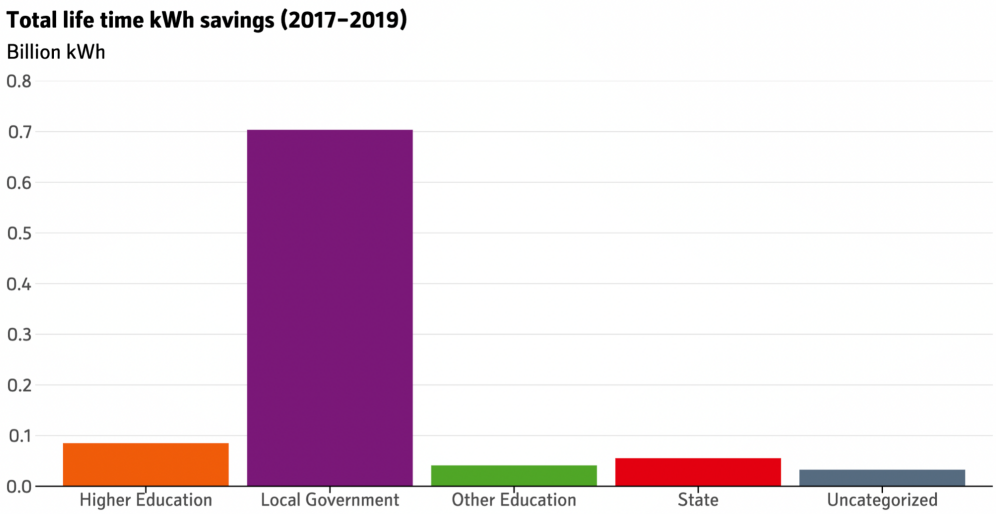

Figure 3. Total lifetime energy savings by category between 2017 and 2019. Federal programs are state partnerships and are included in the state category. K-12 programs are included in the "Other Education" category. Source: CEDARS.

We followed the following steps in our methodology.

1. Preliminary exploration of participation data
    a. Classify and group programs by categories and subcategories with particular interest in local government and K-12 programs
    b. Group programs by spatial regions (counties and cities)
2. Identify the overall differences in participation, investment, and energy savings between groups with the highest and lowest program budget (investment) per capita and total gross first year kilowatt-hour (kWh) energy savings per capita
3. Perform statistical and spatial analysis using economic and demographic information to determine what is driving investment and energy savings in participating groups

Table 2. Classifications of entities filing energy efficiency claims. (Source: Chris Malotte, SCE Business Plan).

State	Federal	Education	Local Governments
State Buildings, State Park Facilities,	Federal Buildings, US Postal Service, Hospitals, Ports, Military Bases,	Higher Education (UC/CSU/CCC) K-12 Education	Cities, Counties, Special Districts, Solid Waste Facilities,

Hospitals, Correctional Facilities	Tribes	Water/Wastewater Facilities, Hospitals, Correctional Facilities

A. Data

In this section, we detail the various data sources used in our study, which include data on energy programs (costs and savings), demographics, rurality, revenue, and K-12 schools.

Energy efficiency program data

Our primary source for data on energy efficiency programs is the California Energy Data and Reporting System (CEDARS). We obtained zip-code level data on energy efficiency programs in the state, along with their costs/budget, energy savings, and location. We used the following data and variables from the CEDARS dataset in our analysis:

- Site information: Site ID, NAICS Code, Site Zip Code, Site City
- Costs: Program Budget
- Savings: Total First Year Gross kWh

To filter for programs specific to local governments, we manually go through the list of programs and classify which programs seem like they are serving or targeting local governments. To filter for K-12 programs, we filter based on the program data's NAICS codes. The NAICS codes we use to obtain energy efficiency data specific to K-12 schools are: 611699, 485410, 611113, and 611112.

Though the CEDARS data is provided at the zip code level, we utilize two spatial resolutions for our analysis: city and county. For our focus on local governments, we conduct one iteration of our regressions with the energy efficiency program variables aggregated to the city level, then we iterate the analysis again with the variables aggregated to the county level. For our evaluation of K-12 programs, we aggregate the energy efficiency data to the county level and only conduct our analysis at the county resolution, as it is difficult to map school districts to cities.

Demographics data

The CalEnviroScreen dataset identifies California communities that are most affected by pollution and that are often especially vulnerable to effects of pollution. The CalEnviroScreen dataset includes 20 indicators that can be grouped into four categories: exposures, environmental effects, sensitive populations, and socioeconomic factors. Indicators are provided at the census tract level. For a given census tract, each indicator has both a score and a percentile of where that census tract's indicator score falls compared to all other census tracts in the state. CalEnviroScreen also calculates a CalEnviroScreen score (CES score) for each census tract by multiplying the pollution burden and population characteristics components together. Finally, CalEnviroScreen uses this combined CES score to provide an assessment of whether the census tract is a disadvantaged community (DAC). If a census tract's CES score falls at or above the 75th percentile, it is classified as a DAC.

Because the CalEnviroScreen data are provided at the census tract level, we aggregate the data to the county and city level. For the CES scores, we calculate each city and each county's average CES score. For DAC proportions, we calculate the proportion of disadvantaged communities within a county or city by dividing the number of DAC-classified census tracts by the total number of census tracts for each county or city.

We obtain data on mean household income and population data from the U.S. Census Bureau. For county-level data, we use the dataset directly provided by the Census Bureau. However, because city-level reporting of census variables is not standard, we use the Census Bureau's tract-level data and CalEnviroScreen's tract-to-city mapping to aggregate the tract-level Census Bureau data to the city level. We also use shapefiles from the Census Bureau's TIGER/Line database for geospatial visualizations.

Rurality data

For our county-level analyses, we use the Index of Relative Rurality that was developed by Purdue University and Mississippi State University (Waldorf and Kim, 2018). The IRR is a continuous, threshold-free, and unit-free measure of rurality that is spatially tracked by counties across the US. This index identifies the dimensions of rurality by population size, density, remoteness, and percentage of built-up area. For our study, we use the median of IRR scores from 2010 and 2000 for each California county.

The USDA Economic Research Service uses rural-urban commuting area (RUCA) codes in order to determine the degree of rurality for census tracts. We use the RUCA code instead of IRR for the city-level analysis because of its census tract-level spatial resolution. Much like the IRR, these codes are also based on population density in addition to urbanization and daily commuting times. Unlike IRR, these codes are on a scale of 1 to 10 (with 10 being the most rural) and are considered a categorical variable.

Revenue data

The California State Controller's Office (SCO) has open data on revenues, expenditures, and other financial data reported by California's counties, cities, special districts, and others. For our study, we use the mean tax revenues by county and by city over the 2016 to 2018 fiscal years. One note worth mentioning is that cities that have energy efficiency program data but are missing revenue data (such as unincorporated territories, for example) are excluded from the analysis.

K-12 data

For our K-12 analysis, we use different datasets from the California Department of Education to develop variables that help us assess if schools are underserved and/or underfunded. One variable we use is the percentage of the student population (within each county) that is eligible for free or reduced-price meals (FRPM). The second variable we use is the percentage of schools (within each county) that qualify for Title I status. Title I is a federal program aimed at providing funding for schools that need funding assistance. The third variable we utilize is the total amount of Local Control Funding Formula (LCFF) entitlement schools within each county receive. Each school’s total LCFF entitlement is a combination of the school’s various revenue sources: state aid, taxes, lottery, and more.

B. Statistical Analysis

T-test Analysis

To evaluate the significance of multiple variables in determining participation in energy efficiency programs, we compare areas with the lowest and highest quartiles of investment and energy savings using Welch’s t-test. These variables represent various socio-economic demographics including DAC proportion, CES score, income, population,

tax revenue, degree of rurality, and race and ethnicity. We then identify variables with statistical significance in difference using p-values.

Regression Analysis

We develop several multivariate regression models to study whether investment and energy savings in energy efficiency programs for participating local governments and K-12 institutions are dependent on certain socio-economic characteristics. We use two different dependent variables for our regression analysis: budget (total and per capita) and energy savings (total and per capita). The regression models can be expressed as follows:

$$\text{Budget/cost; energy savings} = a + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5$$

We cleaned and processed the raw data for each group before the regression analyses. For each group, outliers with a Cook's distance larger than 4/n were removed. Seven counties that did not participate within the period of 2017 to 2019 were omitted for local government programs in our county-level regression analysis. Twenty-six counties that did not participate were omitted from the K-12 programs regression analysis. For our city-level analysis, 119 cities were omitted because there was a lack of demographic information. Further, 125 cities that did not have tax revenue information were also excluded.

Due to the nature of our data, we developed both normal and Poisson forms of generalized linear models (GLMs). The Poisson GLM accounts for the right skew we see in the distribution of budget per capita and kWh saved per capita. We use normal GLMs for y-variables that were log-transformed to resemble a normal distribution. We evaluate the adjusted r square value, coefficients of the variables, and associated p-values to determine the effect of the variables and its significance on the budget of and energy savings from the energy efficiency programs. We also compare models to determine which variables show up consistently as significant.

Geospatial Visualization

Using zip code-specified claims data from the CEDARS dataset, we present geospatial visualizations of multiple variables to understand the spatial heterogeneity of program participation and explanatory variables. Using the county TIGER/Line shapefiles provided

by the Census Bureau, we use the statistical program R to visualize demographic information of energy efficiency program participants by county onto a map.

III. Results

A. T-test Results

T-test results for the local government programs (aggregated at the county-level and cities-level) and K-12 programs are shown in Tables 3, 4, and 5, respectively. Measures of rurality (IRR and RUCA) at the county-level and city-level were significantly different between the top and bottom quartile for per capita program budgets and energy savings (Tables 3 and 4). Local government entities in counties and cities with lower program budgets and energy savings are located in regions classified as more rural. Note that the bottom quartile includes areas that did not participate (budget = 0) and the top quartile includes outliers that were excluded from the regression analysis because of their relatively high program budgets and savings.

Other variables that were significantly different in the county data include the percentage of Asian community as well as population and tax revenue (only for per capita budget) (Table 3). Counties with greater per capita energy efficiency program budgets are larger in population and have greater tax revenues.

Differences in racial demographics were consistent between the two county-level program data -- county-level local government entities and K-12 schools -- but are opposite for the city-level program data. Exclusion of rural areas and the relative affluence of suburban areas classified as relatively rural in the city data may explain these differences. These discrepancies could also be a result of a lack of accurate information on city boundaries and demographics.

For K-12 schools, in addition to the degree of rurality, the mean household income is also significantly different between the counties in the top and bottom quartiles of program budget and energy savings, with the bottom quartile associated with a lower median household income for counties (Table 5). The bottom quartile of counties also has a lower proportion of the Black or African American and Asian communities and a greater proportion of the Native American community, likely reflecting their relative proportions in urban versus rural areas of the state.

Table 3. County t-test summary results. TQ is the top quartile. BQ is the bottom quartile. DAC: disadvantaged community. CES: CalEnviroScreen, IRR: Index of Relative Rurality. Red shaded boxes represent results where there was a significant statistical difference ($p < 0.05$) between the two means.

Variables	TQ kWh per capita	BQ kWh per capita	TQ Budget per capita	BQ Budget per capita
DAC proportion	0.13	0.07	0.13	0.07
CES Score Median	23	18	23	18
IRR	0.43	0.54	0.42	0.58
Population	714054	447597	765074	37814
Tax Revenue	4,767,084,977	2,072,543,947	495,686,094	304,903,948
Mean Household Income	62264	62111	62459	59751
% Black or African American	0.04	0.03	0.04	0.03
% White	0.81	0.83	0.80	0.84
% Asian	0.09	0.03	0.09	0.02
% American Indian or Alaska Native	0.03	0.07	0.03	0.08
% Native. Hawaiian and Other Pacific Islander	0.00	0.00	0.00	0.00

Table 4. City t-test summary results. TQ is the top quartile. BQ is the bottom quartile. DAC: disadvantaged community. CES: CalEnviroScreen, RUCA: Rural Urban Commuting Area, LCFF: Local Control Funding Formula. Red shaded boxes represent results where there was a significant statistical difference ($p < 0.05$) between the two means.

Variables	TQ kWh per capita	BQ kWh per capita	TQ Budget per capita	BQ Budget per capita
DAC proportion	0.14	0.14	0.14	0.14
CES Score Median	22	21	22	21
RUCA	3.2	2.4	3.2	2.8
Population	59600	96915	64707	51915

Tax Revenue	119,272,996	216,500,420	187,627,705	147,967,621
Median Household Income	78,743	81,059	76,990	83,175
% Black or African American	0.03	0.03	0.03	0.03
% White	0.70	0.62	0.71	0.64
% Asian	0.10	0.15	0.10	0.14
% American Indian or Alaska Native	0.01	0.01	0.01	0.01
% Native. Hawaiian and Other Pacific Islander	0.00	0.00	0.00	0.00

Table 5. K-12 t-test summary results. TQ is the top quartile. BQ is the bottom quartile. DAC: disadvantaged community. CES: CalEnviroScreen, IRR: Index of Relative Rurality, LCFF: Local Control Funding Formula. Red shaded boxes represent results where there was a significant statistical difference ($p < 0.05$) between the two means.

Variables	**TQ kWh per capita**	**BQ kWh per capita**	**TQ Budget per capita**	**BQ Budget per capita**
DAC proportion	0.13	0.12	0.15	0.10
CES Score Median	22	22	23	21
IRR	0.38	0.51	0.38	0.52
LCFF per student	973	946	980	934
Percent Eligible for Free and Reduced Meal Plan	0.54	0.63	0.54	0.63
Percent Title 1 Status	0.07	0.06	0.07	0.06
Mean Household Income	78,878	55,752	77,943	55,123
Percent Black or African American	0.04	0.03	0.05	0.02
Percent White	0.77	0.85	0.77	0.86
Percent Asian	0.12	0.04	0.12	0.03
Percent American Indian or Alaska Native	0.02	0.04	0.02	0.05

Percent Native. Hawaiian and Other Pacific Islander	0.00	0.00	0.01	0.00

B. Multivariate Regression Results

To evaluate gaps in energy efficiency program investments and savings for participating local government entities and K-12 schools, we present results of our regression models with 3 different dependent variables -- log of budget or savings, log of per capita budget or savings, and per capita budget for the Poisson model. Within each type of model, the first regression model (1, 3, and 5) includes only those independent variables identified by stepAIC. The stepAIC function selects variables to simplify the model without compromising the performance of the model. Models 2, 4, and 6 include most other independent variables. We excluded some variables that were highly collinear with other variables in the model.

For the county-level analysis of local government programs, IRR was the most consistently significant variable in driving both investment (Table 6) and energy savings (Table 7). Local government programs in more rural counties are likely to have lower total investments and energy savings. However, programs in rural counties are also likely to have higher per capita investments and energy savings. Some models also show that lower tax revenue per capita results in greater per capita investments and savings.

Table 6. County investment regression summary results.

Investment Regression Results (County)

	Dependent variable:					
	Log of Budget normal		Log Budget Per Capita normal		Budget Per Capita Poisson	
	(1)	(2)	(3)	(4)	(5)	(6)
Revenue		-0.000				
		(0.000)				
Revenue per Capita			-0.0001	-0.0001*		-0.0001***
			(0.00005)	(0.0001)		(0.00003)
Income		0.00002	0.00001*	0.00001		0.00001
		(0.00002)	(0.00001)	(0.00001)		(0.00000)
IRR	-13.707***	-12.443***		3.773*		3.113***
	(2.145)	(4.402)		(2.145)		(1.145)
DAC Proportion		1.547		-0.337		-0.595
		(1.185)		(0.666)		(0.376)
Percent of On-bill Financing		0.007	0.010	0.008		0.007**
		(0.012)	(0.006)	(0.006)		(0.003)
Population			-0.00000***		-0.00000***	
			(0.00000)		(0.00000)	
Constant	19.580***	17.707***	1.653***	-0.194	2.011***	0.609
	(0.960)	(2.926)	(0.518)	(1.429)	(0.071)	(0.762)
Observations	48	48	48	48	48	48
Akaike Inf. Crit.	168.587	173.027	109.374	116.935	340.135	343.131

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7. County energy savings regression summary results.

Energy Savings Regression Results (County)

	Dependent variable:					
	Log of kWh normal		Log Kwh Per Capita normal		kWh Per Capita Poisson	
	(1)	(2)	(3)	(4)	(5)	(6)
Revenue		-0.000				
		(0.000)				
Revenue per Capita			-0.0002***	-0.0002**	-0.0002***	-0.0002***
			(0.0001)	(0.0001)	(0.00003)	(0.00003)
Income		0.00001	0.00002**	0.00002		0.00001**
		(0.00002)	(0.00001)	(0.00001)		(0.00000)
IRR	-21.785***	-17.493***		3.177		2.023**
	(3.759)	(4.891)		(2.661)		(0.863)
DAC Proportion		1.675		-0.272		-0.603**
		(1.317)		(0.826)		(0.296)
Percent of On-bill Financing		-0.009		-0.001		-0.002
		(0.013)		(0.008)		(0.003)
Population	-0.00000*		-0.00000***		-0.00000***	
	(0.00000)		(0.00000)		(0.00000)	
Constant	23.913***	20.891***	2.388***	0.811	3.544***	2.144***
	(1.862)	(3.252)	(0.632)	(1.773)	(0.192)	(0.591)
Observations	48	48	48	48	48	48
Akaike Inf. Crit.	177.582	183.154	127.522	137.619	495.169	509.197

Note: *p<0.1; **p<0.05; ***p<0.01

For city-level analysis, RUCA codes (measure of rurality), the percentage of on-bill financing, and the percentage of resource-type claims are significant variables driving both investment (Table 8) and energy savings (Table 9).

Table 8. Cities investment regression summary results.

Investment Regression Results (Cities)

	Dependent variable:					
	Log of Budget normal		Log Budget Per Capita normal		Budget Per Capita Poisson	
	(1)	(2)	(3)	(4)	(5)	(6)
Revenue	0.000***	0.000*				
	(0.000)	(0.000)				
Revenue per Capita			0.0001***	0.0001***	0.0001***	0.0001***
			(0.00004)	(0.00004)	(0.00001)	(0.00001)
Income		-0.00000		-0.00000	-0.00001***	-0.00001***
		(0.00000)		(0.00000)	(0.00000)	(0.00000)
RUCA		-0.027	0.171***	0.153***	0.145***	0.130***
		(0.052)	(0.046)	(0.050)	(0.009)	(0.010)
DAC Proportion		-0.050		-0.250	-0.879***	-0.831***
		(0.355)		(0.341)	(0.089)	(0.088)
Percent of On-bill Financing	0.014***	0.014***	0.014***	0.014***	0.006***	0.007***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
Percent of Resource Programs	-0.065**	-0.064**	-0.061**	-0.061**	-0.048***	-0.047***
	(0.027)	(0.027)	(0.026)	(0.026)	(0.002)	(0.002)
Population		0.00000	-0.00000**	-0.00000**		-0.00000***
		(0.00000)	(0.00000)	(0.00000)		(0.00000)
Constant	17.726***	17.760***	6.472**	6.817***	6.750***	6.815***
	(2.685)	(2.724)	(2.588)	(2.614)	(0.228)	(0.228)
Observations	288	288	288	288	288	288
Akaike Inf. Crit.	1,093.644	1,100.534	1,074.438	1,077.172	2,815.241	2,789.207

Note: *p<0.1; **p<0.05; ***p<0.01

Table 9. Cities energy savings regression summary results.

Energy Savings Regression Results (Cities)

	Dependent variable:					
	Log of kWh normal		Log Kwh Per Capita normal		kWh Per Capita Poisson	
	(1)	(2)	(3)	(4)	(5)	(6)
Revenue	0.000***	0.000*				
	(0.000)	(0.000)				
Revenue per Capita			0.0001*	0.0001*	0.0001***	0.0001***
			(0.00003)	(0.00003)	(0.00001)	(0.00001)
Income		-0.00000		-0.00000	-0.00001***	-0.00001***
		(0.00000)		(0.00000)	(0.00000)	(0.00000)
RUCA		0.030	0.157***	0.131***	0.156***	0.144***
		(0.061)	(0.032)	(0.035)	(0.007)	(0.008)
DAC Proportion		-0.038	-0.361*	-0.432*	-0.986***	-0.936***
		(0.416)	(0.217)	(0.240)	(0.070)	(0.070)
Percent of On-bill Financing	0.016***	0.016***	0.008***	0.008***	0.005***	0.005***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)
Percent of Resource Programs		0.019		0.018		0.031*
		(0.032)		(0.018)		(0.017)
Population		0.00000		-0.00000		-0.00000***
		(0.00000)		(0.00000)		(0.00000)
Constant	11.455***	9.455***	1.394***	-0.064	2.492***	-0.536
	(0.143)	(3.197)	(0.144)	(1.838)	(0.071)	(1.680)
Observations	288	288	288	288	288	288
Akaike Inf. Crit.	1,183.908	1,192.725	872.262	874.308	4,861.875	4,827.116

Note: *p<0.1; **p<0.05; ***p<0.01

For K-12 programs, the percentage of eligible students for a free and reduced meal plan, the percentage of Title 1 schools, and DAC proportion are significant variables driving investment or energy budgets (Table 10). The lower the percentage of eligible students for a free and reduced meal plan is, the smaller is the total or per capita energy budget. In contrast, lower percentage of title 1 schools are correlated with lower investments. Lastly, greater DAC proportions in counties are associated with lower energy efficiency investments for participating counties. For energy savings, only the Poisson model showed some independent variables to be significant -- percentage of eligible students for a free and reduced meal plan, LCFF, IRR, and DAC proportion (Table 11).

Table 10. K-12 investment regression summary results.

Investment Regression Results (K12)

	Dependent variable:					
	Log of Budget normal		Log Budget Per Student normal		Budget Per Student Poisson	
	(1)	(2)	(3)	(4)	(5)	(6)
Percent Eligible for Free or Reduced Meal Plan	10.205***	10.999***	2.292**	2.662		3.658***
	(3.281)	(3.774)	(1.019)	(1.656)		(1.283)
Percent of Title 1 Schools	-16.573**	-20.090**	-8.308***	-10.127**	-19.686***	-32.936***
	(7.691)	(8.140)	(2.834)	(4.437)	(5.123)	(6.297)
LCFF	0.000***	0.000***				
	(0.000)	(0.000)				
LCFF per student				0.0001		0.001***
				(0.0003)		(0.0002)
Income	0.0001***	0.00004		0.00000		
	(0.00002)	(0.00003)		(0.00001)		
IRR		-4.799		-0.756	5.714***	-1.951
		(4.649)		(1.952)	(1.808)	(2.089)
DAC Proportion		-2.942	-1.676**	-1.737**		-2.346**
		(1.952)	(0.738)	(0.833)		(0.999)
Percent of On-bill Financing		-0.001		-0.006		-0.030*
		(0.012)		(0.005)		(0.016)
resource						
Constant	0.496	4.137	0.369	0.368	-0.620	0.817
	(3.310)	(5.458)	(0.574)	(2.341)	(0.986)	(1.050)
Observations	31	31	31	31	31	31
Akaike Inf. Crit.	122.563	125.157	67.155	73.271	139.775	123.014

Note: *p<0.1; **p<0.05; ***p<0.01

Table 11. K-12 energy savings regression summary results.

Energy Savings Regression Results (K12)

	Dependent variable:					
	Log of kWh normal		Log Kwh Per Student normal		kWh Per Student Poisson	
	(1)	(2)	(3)	(4)	(5)	(6)
Percent Eligible for Free or Reduced Meal Plan	11.252	13.381	1.871*	1.984	2.383***	3.081***
	(7.591)	(8.936)	(1.094)	(1.761)	(0.907)	(1.043)
Percent of Title 1 Schools	-3.013	-14.936	-2.707	-4.920		-4.168
	(16.061)	(19.271)	(3.918)	(4.718)		(4.823)
LCFF		0.000				
		(0.000)				
LCFF per student			-0.0005	-0.0004	-0.001***	-0.001**
			(0.0003)	(0.0003)	(0.0002)	(0.0003)
Income	0.0001	0.0001		-0.00000		
	(0.0001)	(0.0001)		(0.00001)		
IRR		1.851		-1.636		-2.594**
		(11.007)		(2.076)		(1.303)
DAC Proportion		-4.185	-1.267	-1.499	-1.451**	-1.874**
		(4.622)	(0.791)	(0.886)	(0.731)	(0.817)
Percent of On-bill Financing		0.017		-0.003		-0.008
		(0.028)		(0.006)		(0.007)
resource						
Constant	-2.193	-3.930	0.761	1.660	0.534	1.355**
	(7.696)	(12.922)	(0.619)	(2.489)	(0.543)	(0.684)
Observations	31	31	31	31	31	31
Akaike Inf. Crit.	174.520	178.590	72.297	77.085	146.746	148.239

Note: *p<0.1; **p<0.05; ***p<0.01

C. Spatial Characterization

We mapped different variables to see if there are any discernible geospatial patterns in budget, energy savings, rurality, or socioeconomic characteristics in our analysis. In Figure 4, we map the budget by county on the left and the lifecycle energy savings on the right. The highest budgets are located in highly populated counties like San Francisco, Los Angeles, and San Diego. The distribution of lifecycle savings appear to be more distributed, with the highest savings occuring in the more coastal counties. When comparing with the map of IRR by county in Figure 5, we can see that the counties with the highest IRR scores (lighter colors), which represent the more rural counties, tend to have the lowest efficiency program budgets. The scatterplots on the right of Figure 5 also show this trend between higher rurality scores and lower budgets (as well as lower energy savings, to a slightly lesser degree).

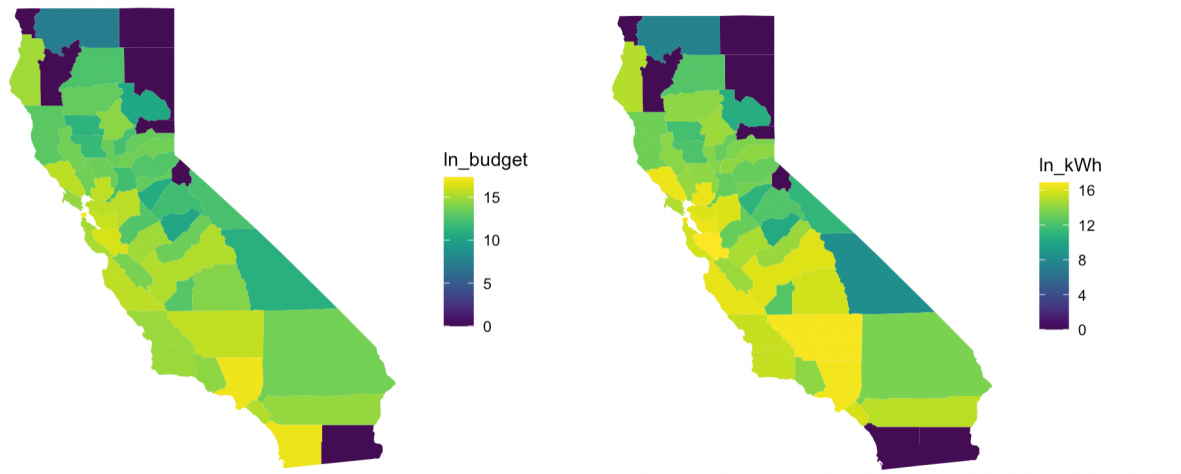

Figure 4. Spatial mapping of budget (in million USD) and lifecycle energy savings (in units of million kWh) for all California counties. Note that the values are on a natural log scale.

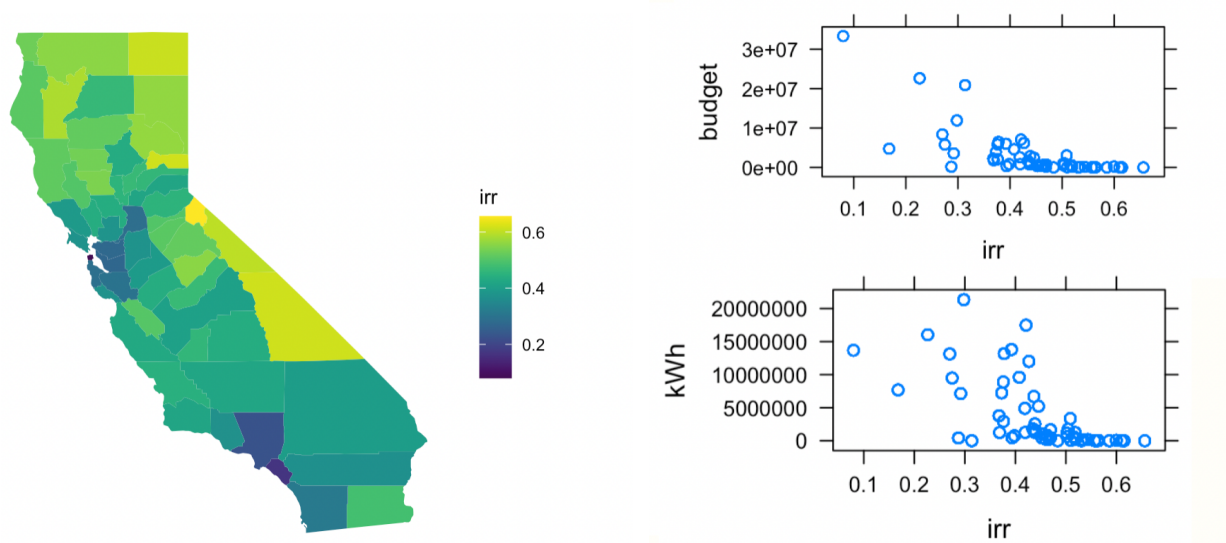

Figure 5. Spatial mapping of IRR scores for all California counties and its correlation to budget (in units of million USD) and lifecycle energy savings (in units of million kWh).

In Figure 6, we display the spatial distribution of K-12 variables such as the percentage of Title I schools within each county (left) and the percentage of students eligible for free or reduced-price meals (right). For the percentage of Title I schools, while we do see that the populous counties such as San Diego and Los Angeles are on the higher end of percentages, some of the more rural counties in northern California (Mendocino, Sutter, and Butte) actually have slightly higher percentages of Title I status schools. We can also see that counties in the Central Valley, which tend to be more rural as well, tend to have the highest percentages of students eligible for free or reduced-price meals.

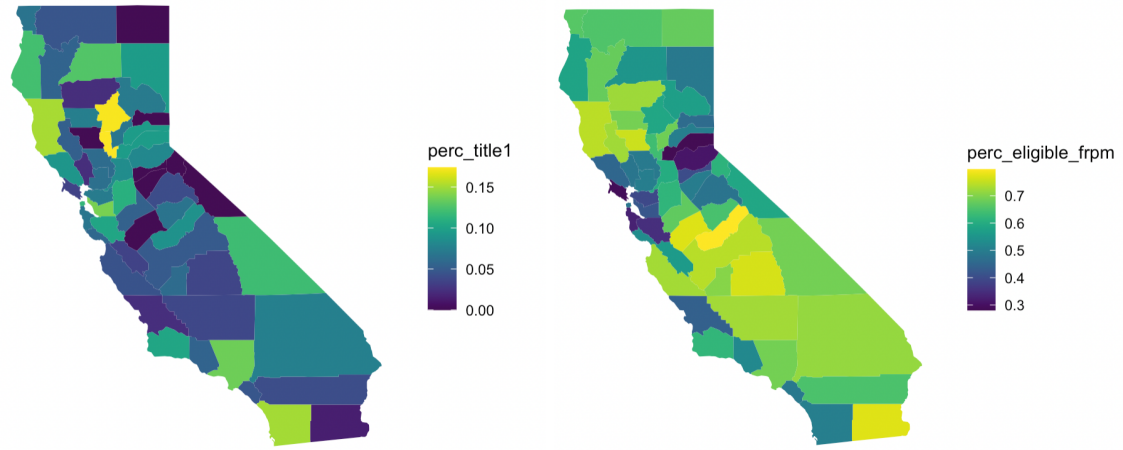

Figure 6. Spatial mapping of the percentage of Title 1 schools (perc_title1) and the percentage of eligible students for free and reduced-price meals(perc_eligible_frpm) for all California counties.

IV. Conclusions

Our results show that rurality plays an important role in determining participation in energy efficiency programs and the level of energy efficiency investments and energy savings. Program participation in more rural counties and cities tend to have smaller investments and lower energy savings. These differences or “gaps” between rural and urban counties and cities could be due to a lack of resources, assets, or exposure to energy efficiency programs within more rural communities.

On the finer spatial scale of cities, utility support through on-bill financing and non-resource programs contribute to the drivers of investment and energy savings. For K-12 schools, school poverty proxy variables including the percentage of eligible students for a free and reduced meal plan and the percentage of Title 1 schools explain differences in investment and savings.

A. Limitations

Our study examines energy efficiency programs from the year of 2017 to 2019. We do not have access to information on program participation prior to these years. Prior years’ data are not available due to structural changes in how public utilities reported energy efficiency program information in the past. Our conclusions assume that past participation patterns are similar to those in 2017 - 2019.

Some public sector entities have likely participated in programs classified as commercial instead of public sector. However, we were not able to identify those programs and separate information for public sector participants from the larger commercial programs. Therefore, we cannot include these programs in our study and limit our scope to programs that are strictly categorized as public sector.

To evaluate local government program participation at a finer spatial resolution, we analyzed the local government energy efficiency program data at the city-level. However, we omitted 244 cities out of 536 from the regression dataset due to a lack of demographic and tax revenue data, which likely affected the results of our city-level analysis.

Our analysis shows only the strength and character of the relationship between certain variables to investment and energy savings. Additional surveys and interviews of participants and stakeholders, especially in underserved areas must be included in future research in order to fully understand the barriers preventing participation.

V. References

Waldorf, B., Kim, A. (2018). The Index of Relative Rurality (IRR) : US County Data for 2000 and 2010. Purdue University Research Repository. doi:10.4231/R7959FS8