USC Sol Price Capstone (PPD 546): Final Memo
Nicholas Cain, Ph. D
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ENERGY EQUITY TEAM
Dairou Wang, Eunice Zordilla, Elizabeth Pereda, Monina Letargo, Tianfang Guo

EXECUTIVE SUMMARY

Energy efficiency has become the nation's third-largest electricity resource and is the cheapest and fastest way to cut harmful pollution. In California, where nearly half of the country's greenhouse gas emissions are produced, there is a need to increase energy efficiency (Friedrich, Ge, & Pickens, 2019). The Clean Energy and Pollution Reduction Act (SB350) directed the California Energy Commission (CEC) to decrease GHG emissions and establish targets for increased renewable electricity procurement in California (California Energy Commission, 2016). However, combined natural gas and electricity benchmarks indicate the State will be approximately 20 percent short of its residential energy efficiency and savings goals (Kenny et al., 2019). Currently, the Energy Commission is collaborating with other state agencies such as the California Public Utilities Commission (CPUC), the California Air Resource Board (CARB), and the California ISO) to meet these goals.

The Natural Resources Defense Council (NRDC) as part of the California Energy Efficiency Coordinating Committee seeks to understand whether geographic or sociodemographic factors impact residential energy efficiency program participation. The purpose of this study is to determine whether California residential EE program benefits are distributed equitably among various customer groups, particularly those that we suspect may be underserved. Existing initiatives such as the California Alternate Rates of Energy (CARE) and the Family Electric Rate Assistance (FERA) programs are designed to increase energy equity for low-income customers. The NRDC has requested a participation gap analysis focusing on non-low-income groups, or households who do not qualify for low-income energy assistance programs.

The scope of this study includes 1,457 zip codes, located within the service territory of California's four major investor-owned utilities, having a median household income greater than the maximum CARE/FERA threshold for a family of two. We utilized spatial and statistical analysis to determine significant relationships between aggregated participation and Census tract data. The level of EE program participation among non-low-income customers varies throughout the State, with concentrations of higher participation occurring throughout Central and Southern California. Further examination reveals significant differences in participation among rural and urban communities, renters and homeowners, ethnic groups, language groups, and native- and foreign-born residents.

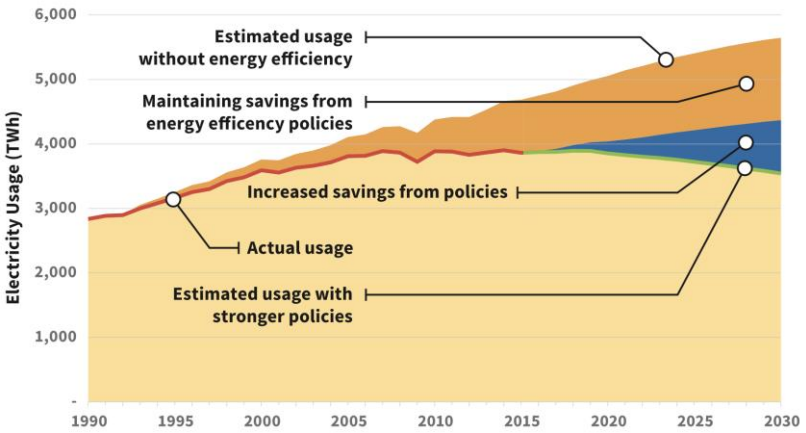
I. CONTEXT: Global Climate Change & Greenhouse Gases

The increasing occurrence of droughts and devastating fires in California illustrates the local effects of climate change (*Statewide Summary Report*, 2018). One of the key resources available to combat climate change is energy efficiency, which reduces the need to generate electricity, natural gas, or other fuels and, thus, over time reduces the amount of greenhouse gases released into the atmosphere that contribute to global warming (Carter, 2016). Senate Bill 350 (SB 350) codifies California's goal to achieve a statewide cumulative doubling of energy efficiency savings and demand reductions in electricity and natural gas by 2030. It also directed the California Energy Commission (CEC) to set annual targets to achieve the goal of increasing renewable electricity

procurement from 33 percent in 2020 to 50 percent by 2030 (California Energy Commission, 2016).

Energy efficiency has become the nation's third-largest electricity resource and is the cheapest and fastest way to cut harmful pollution. The American Council for an Energy-Efficient Economy (ACEEE) provides evidence regarding how much the US and California, specifically, has already benefited from energy-saving programs (Molina, Kiker & Nowak, 2016). Figure 1 illustrates how energy efficiency has become an important resource to save money and address climate change by reducing harmful pollution.

Figure 1 Estimated savings from both maintaining & increasing EE policies through 2030



(Molina, Kiker & Nowak, 2016)

Energy savings are driven mostly by residential and commercial sector programs (Kenny et al., 2019). However, based on 2017 projections, California is on a trajectory to fall below the SB350 goals across all sectors. In 2019, the CEC implemented the California Energy Efficiency Action Plan and recommended greater program participation in residential and commercial sectors, along with introducing more EE programs to the market.

II. PURPOSE & GOAL

In order to meet residential sector goals, California must ensure all possible utility consumers have the opportunity to utilize energy more efficiently. The purpose of this study is to determine whether EE program benefits are equitably distributed among all residential customer groups. More equitable distribution of EE program benefits can reduce energy costs among underserved populations and further reduce the overall demand for energy production, not accounting for potential energy rebound effects.

This research study will assess the state of participation in residential energy efficiency programs funded by California's major investor-owned utilities (IOUs). In doing so, we can identify whether gaps in participation exist among residential customers based on geographic area and/or specific socio-demographic characteristics. In other words, we want to know which customers benefit more or less from the provided programs. We expect that relevant findings will inform future

decisions regarding additional research and EE program design to improve program reach and participation and ensure a more equitable distribution of program benefits.

III. DEFINITIONS & BACKGROUND

Energy Efficiency programs are intended to provide equitable benefits to the public — but these programs may also inadvertently contribute to the growing gap between rich and poor. For example, households who participate in energy efficiency (EE) programs can reduce their energy consumption and overall household spending — however, participation in EE programs may require capital to invest in efficient equipment.

- *What is Energy Efficiency?*
  Energy efficiency is defined as the "method of reducing energy consumption by using less energy to attain the same amount of useful output" (EnergySage, 2020). When consumers utilize energy more efficiently, their existing demand for energy decreases and allows utilities to generate new energy at a lower cost.

- *What is Equity?*
  Equity is often confused with the term "equality," which means sameness and, incorrectly, that we all have equal access, treatment, and outcomes. True equity implies that an individual may need to experience or receive something different (not equal) to maintain fairness and access (Diversity, Equity & Inclusion 2020). Equity is bridging the social, economic, and cultural divide. It seeks to ensure everyone reaps the awards, not just specific groups.

- *What is Equity in relation to Energy Efficiency?*
  Energy efficiency remains out of reach for many Americans. Prioritizing equity in energy efficiency programs begins by identifying groups historically underserved by energy efficiency renewable energy investments and the disparate impacts caused by examining deeper through various sociodemographic variables (ACEEE, 2019). Equity intertwined with energy efficiency is about distributing the risks and the benefits fairly. “Energy efficiency is not a goal in itself, but only a means to the end of overall economically efficient (and equitable) resource allocation” (Jaffe, Newell, & Stavins, 2004).

IV. RESIDENTIAL PROGRAMS

Four major investor owned utilities (IOUs)[1] administer residential energy efficiency programs for approximately 75% of California households (California Energy Commission, 2019). A variety of programs exist to help homeowners meet current energy efficiency building codes and appliance standards. EE programs can be categorized as upstream, midstream, or downstream depending on who receives the initial incentive. Downstream and midstream delivery models provide the most direct benefit to households. The downstream model focuses on the customers (homeowners); for

[1] The four major IOUs are: SDG&E, Pacific Gas and Electric, SoCal Gas, Southern California Edison, Bay Area Regional Energy Network, SoCal Regional Energy Network, and San Diego Gas and Electric

example, the purchase of an Energy Star-rated appliance or smart thermostat is eligible for a rebate incentive. Whereas the midstream model focuses on distributors by providing a discount on eligible equipment that is then passed on to customers; typically for energy efficiency home upgrades such as new window or heating and air conditioning system installations.

V. ENERGY BURDEN AND POTENTIAL BARRIERS

Various motivations related to personal ideologies or preferences can influence an individual to participate in an EE program (Lazar & Colburn, 2013). In many cases, circumstances or barriers may influence a customer's behavior and decision not to participate in EE programs. These barriers include low home-ownership rates, complex customer needs, insufficient access to capital, building age, and remote or underserved communities (CEC, 2016). It is also possible that barriers related to ethnicity, primary language, age, education, and internet access, plus income level may affect participation rates.

EE programs are an important resource to reduce a person's energy burden, particularly among those who make less than the living wage. Energy burden is the percentage of one's income spent on energy costs. Approximately 25% of all U.S. households experience a high rate of energy burden (ACEE, 2019). Customers whose income is greater than the poverty level, and less than the living wage, are a good example of one population that may be underserved by EE programs. Many EE programs included in our study require an upfront investment that may not be feasible for customers who do not qualify for low income assistance. If a household cannot qualify as low-income and is not able to afford energy efficient home improvements or upgrades, it cannot take advantage of other EE programs and respective benefits. Households such as these are hard to reach due to their income status.

VI. HYPOTHESIS AND STRUCTURE OF REPORT

Based on informational interviews with the NRDC and preliminary literature review, we hypothesize that program benefits are not equitably distributed and may not be reaching hard-to-reach customers like lower-income residents, those who do not speak English as their primary language, and those residing in rural areas. Additionally, we anticipate that customers with a higher income level and who reside in more metropolitan areas will show higher participation, investment, and energy savings as compared to customers in harder-to-reach-locations. The following sections will explore available data provided by the CPUC and discuss our approach to identify participation gaps among residents within the service territory of the four major IOUs in California. Findings based on the data analysis will be presented by means of visualizations to show geographic locations of participants by zip code and relationships between select socio demographic variables. Additional evidence and confirmation of statistical significance will be provided to support spatial observations.

VII. METHODOLOGY

The NRDC has requested a participation gap analysis among all residential energy efficiency programs. Our research goal is to determine whether energy efficiency program benefits are distributed equitably among residential customers. To do so, we seek to answer the following two research questions:

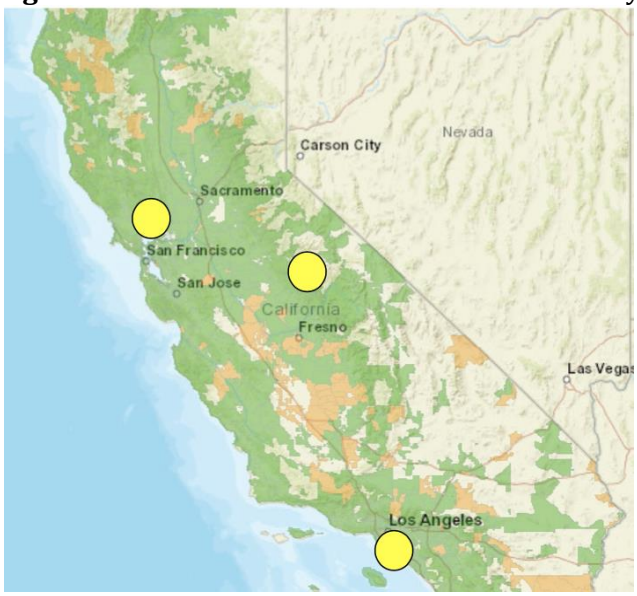
1. *Are there gaps in program participation by geographic areas?*

2. *Are there gaps in program participation by socio-demographic groups?*

DATA & SCOPE

Our area of study includes all California zip codes located within the IOU service territory (see Figure 2). The CARE threshold for a household of two is $34,480, the FERA maximum is $43,440 (CPUC, 2020). Since our focus is on non-low-income participants, we exclude zip codes that have a median household income that is at or below the qualifying income level for CARE/FERA low income assistance programs. The study population are households within zip codes that have a median household income level of $43,441 or greater; and are categorized as non-low income, shown below in green.

Figure 2 Investor Owned Utilities Service Territory



(Source: ACS, 2018; CEDARS, 2019)

We utilized two main sources of data to identify and analyze residential energy efficiency program participation. Due to the proprietary nature of the study, we relied on the NRDC to coordinate access to CPUC's EE program claims data. Utilizing the CEDARS online database, we extracted 2019 1st quarter participation records for residential programs that target non-low-income households. Ultimately, we were able to develop an aggregated dataset of program activity based on participation claims per household at the zip code level. Table 1 illustrates the methodology of data collection and analysis to address our two research questions.

Table 1 Data Collection & Analysis Methods to Address Research Questions

Research Question	Program	Indicator	Measurement	Data Sources	Data Analysis
1 Are there gaps in program participation by geographic areas?	All Residential Programs of the Major IOUs	· Participation	· # of units by zip code	· P.A.'s (CEDARS), Tiger/Line shapefiles	GIS Spatial Analysis, hotspot analysis by GeoDa, and Statistical Correlation Analysis
		· Investment	· Dollar gross incentive	· P.A.'s (CEDARS)	
		· Energy Savings	· kWh/therms saved per household	· P.A.'s (CEDARS)	

Table 1 (Continued) Data Collection & Analysis Methods to Address Research Questions

2	Are there gaps in program participation by socio-demographic groups?	All Residential Programs of the Major IOUs	· Participation	· # of household by income type, ethnicity, primary language, education	· P.A.'s (CEDARS) U.S. Census Bureau ACS 5-yr estimates	GIS Spatial Analysis, hotspot analysis by GeoDa, and Statistical Correlation Analysis
			· Investment	· Dollar gross incentive	· P.A.'s (CEDARS)	
			· Energy Savings	· kWh/therms saved per household	· P.A.'s (CEDARS)	

For each research question we provide the programs to be included, indicators of participation, the unit by which they will be measured, data sources, and the type of analysis to be applied. As previously mentioned, the dataset includes all residential EE programs and provides totals for participation, investment, and energy savings based on the stated units of measurement. Secondly, we applied demographic, social, housing, and economic characteristics to each zip code by extracting tract level data from the U.S. Census Bureau's ACS 2018 5-year estimates and merging it with our aggregated EE program claims data. We selected a variety of attributes to identify EE program participants. Specifically, we analyzed the following zip code characteristics: population size, ethnicity, median household income, attained level of education, household language, household type, place of birth, and age.

Because we include all programs, which have specific outputs, we must also identify a standard unit by which to measure program participation. We selected the dollar amount of gross incentive for program investments as the most universal of participation indicators, then divided each total amount by the number of households within each respective zip code (total investment/total number of households = program activity level).

SPATIAL ANALYSIS

We performed spatial data manipulation using geographical information systems (GIS), and spatial modeling to identify relationships and predict outcomes in a spatial context. By analyzing data at the zip code level, we were able to determine where EE program claims data intersect with socio demographic characteristics so that we can identify participants.

We created maps by using the Python geopandas module and applied hotspot analysis by using GeoDa. Our first map illustrates the geographic area of the service territory of the four major IOUs. Tiger/Line shapefiles for California's zip code tabulation areas provide geometry information at zip code tabulation areas level. We then imported the selected socio-demographic dataset into GeoDa and merged it with the California zcta shapefile to generate quantile maps. Utilizing all non-low-income zip codes, we first created a 5-quantile map of participation rate. We then used Local G* to run a hotspot analysis. A hotspot can be defined as an area with a higher concentration of events than the expected number given a random distribution of events ("What is Hotspot Analysis?", 2016). In Geoda, we then mapped the data into 'low', 'high', 'not significant', and 'undefined'. We repeated the same procedures on selected socio-demographic variables and compared the mapping results with the hotspot program activity rate map.

In terms of the spatial analysis of overall participation, all zip codes are evenly distributed and provide a general representation of varying levels of program activity levels. Among all non-low-income levels, the program activity level ranges from 0 to 1309. Zip codes with an activity level of 12.2 or higher are considered outliers; this accounts for 125 zip codes. We chose not to remove outliers from the spatial analysis as it would exclude major metropolitan areas and generate an incomplete visualization of zip codes with the highest participation levels.

STATISTICAL ANALYSIS

We used regression analysis to discover the relationships between selected socio-demographic variables and participation and compare the strength of those relationships in terms of program activity. We used SPSS and Python to run descriptive analysis, regression analysis and T-tests of the following data:

- Rural and Urbanized zip codes defined by population
- Ethnic Distribution: White, Black /African American, Asian, and Hispanic/Latino
- Language: Percentage of households whose primary language is not English
- Household type: Percentage of renter or owner occupied in the area
- Age of the home: Percentage of homes constructed in 1990 and later
- Place of Birth: Percentage of native and foreign born
- Age: Percentage of Residents 65 years old and over as well as median age of all the participants

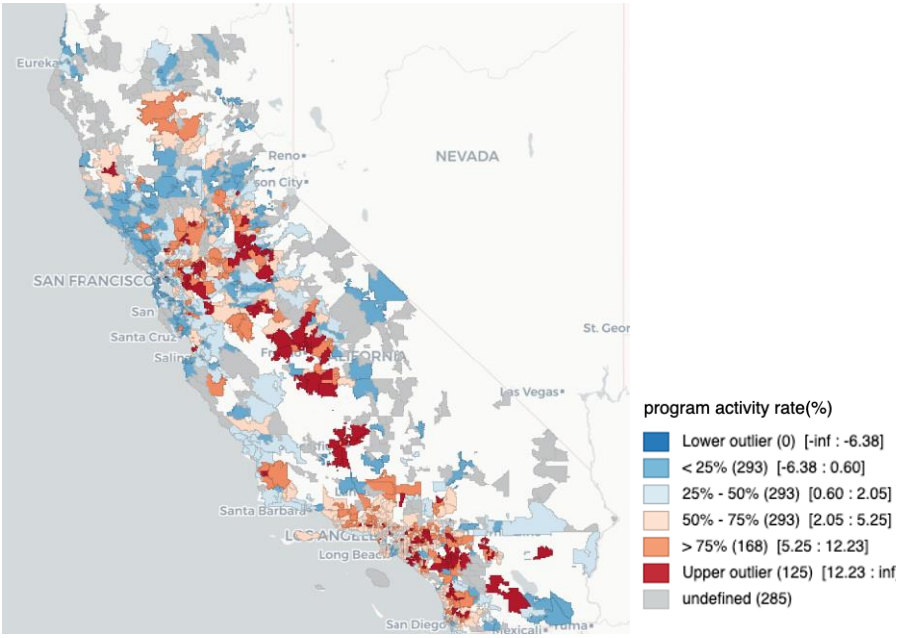
The original data from ACS was first filtered by missing values and extreme values. Among 1769 zip codes, 194 zip codes are beyond the program scope of services and have no data for basic research and are excluded, leaving a total of 1575 zip codes. We also excluded those that are not serviced by the IOUs. Consistent with the spatial analysis dataset, we excluded the zip codes whose median household income is at or below $43,440 to generate our non-low-income dataset.

Initial analysis was performed with all non-low-income zip codes. However, to ensure observation of true activity among sociodemographic data across zip codes, we remove all outliers with a program activity level below -6.37 or above 12.22. We then performed another round of analysis with the remaining 1047 zip codes. The results, while still similar to the initial analysis, showed clearer trends.

VIII. FINDINGS AND ANALYSIS

Spatial analysis of 1457 non-low-income zip codes show that participation is concentrated throughout Central and Southern California (see Figure 3). For this visualization, the total number of zip codes was divided into quantiles representing five levels of participation as shown in the key to figure 6. The color coding represents different program activity ranges, where the darkest shading of blue represents the lowest participation, and the darkest shading of red represents the highest participation.

Figure 3 Quantile Map of Residential Energy Efficiency Program Activity



(Source: ACS, 2018; CEDARS, 2019)

There are significant areas throughout Central and Southern California that show high to highest program activity. At the same time, areas with low and lowest participation are spread mainly throughout coastal regions in Northern California. This may be potentially due to a given zip code's climate or geographic terrain. While we have included approximately 89% of Zip Codes in the IOU service territory, there are gaps throughout that are representative of zip codes that have reported program activity, however due to lack of data they cannot be identified as low income or non-low-income.

OVERALL DEMOGRAPHIC OF POPULATION

The demographic characteristics among zip codes included in the study are relatively similar to that of California's overall demographic with some small variations. We see that the distribution of ethnicity is similar in that non-Hispanic whites make up the largest group among all participants. Hispanic or Latino participants comprise more than one third of all participants. There are 50% less Asian participants than Hispanic or Latino participants. Black or African American participants are largely underrepresented comprising only 5.5% of the total participant population (see Table 2

Table 2 Distribution of Ethnicity Among Population

Ethnicity	**Participants**	**CA**
White	60.6%	71.9%
Hispanic/Latino	34.8%	39.4%
Asian	15.6%	15.5%
Black/African American	5.5%	6.5%

(Source: ACS, 2018; CEDARS, 2019)

The percentage of participants that achieved a bachelor's degree or higher was slightly higher than that of the entire State population (see Table 3). However, the level of education was not a significant factor.

Table 3 Attained Level Among Population

Educational Level	**Participants**	**CA**
Bachelor or Higher	35.2%	33.3%
High School or Higher	85%	82.9%

(Source: ACS, 2018; CEDARS, 2019)

The percentage of participants who spoke English less than very well, or whose home language was not English, is lower compared to the population of California (see Table 4). Statistical analysis showed that program activity was similar among the two language groups and language was not a significant factor.

Table 4 Language Spoken Among Population

Language Level	**Participants**	**CA**
English Less than Very Well	16.5%	18.6%
Language at Home Not English	41.5%	44.1%

(Source: ACS, 2018; CEDARS, 2019)

In terms of Age distribution, only 14.2% of participants is 65 years old and over, which illustrates a potential gap between the elder group and others in participation (see Table 5). In comparison to the whole population, the average age distribution is similar among participants.

Table 5 Age Distribution Among of Population

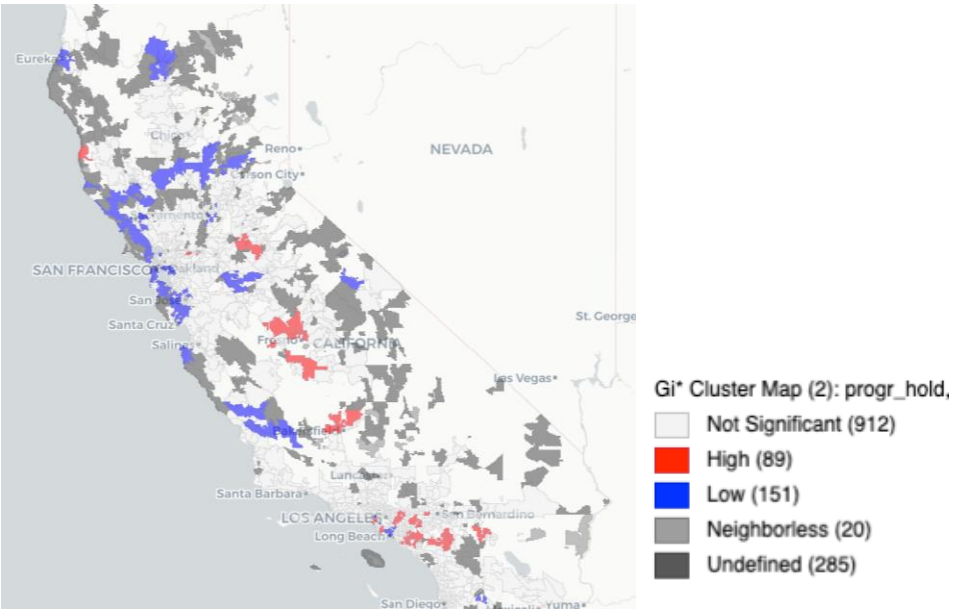
Age	**Participants**	**CA**
65 Years and Over	14.2%	14.8%
< 65 Years	85.8%	85.2%

(Source: ACS, 2018; CEDARS, 2019)

VISUALIZATION OF GEOGRAPHIC ANALYSIS

Analysis of the highest and lowest level of participation among non-low-income zip codes, shows that participation is most noticeable in Central California and Southern California, particularly in the San Joaquin Valley and throughout the Greater Los Angeles Area. Among the 1457 non-low-income zip codes, approximately 16% are identified among the hot spots (Figure 4).

Figure 4 Hotspot Map with clusters of Higher/Lower participation

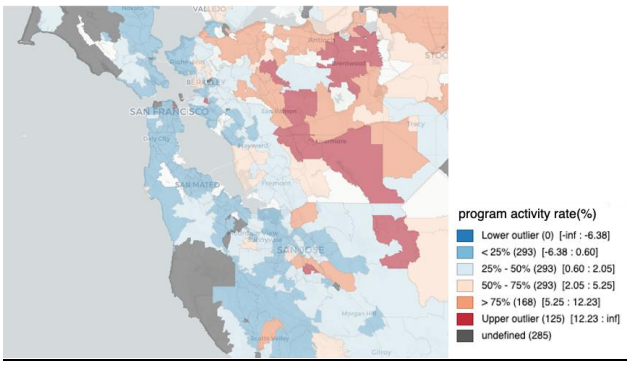


(Source: ACS, 2018; CEDARS, 2019)

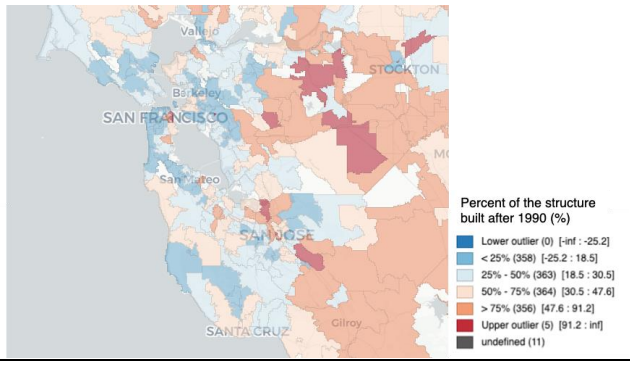
Approximately 6% percent of zip codes were among those with the Highest Participation, which included 89 zip codes with program activity level of 20 or more. Some of the Zip Codes showing the highest level of program activity are Whittier, Irvine, West Covina, Chino, Torrance, and Fresno. Whereas approximately 10% of zip codes had the lowest participation, which included 151 zip codes with an activity level of less than 0.2. Among urban zip codes, San Francisco, Bishop, Stanford, Hilmar, Quincy, and Long Beach were among those that showed the lowest program activity level. Occidental, Maxwell, and Browns Valley were among rural zip codes in the lowest quantile of program activity level.

Figure 5 Comparison of Bay Area Program Participation Map and Age of Residence Map

a.



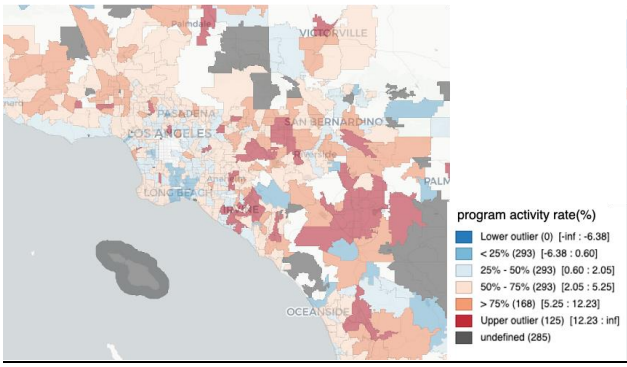
b.



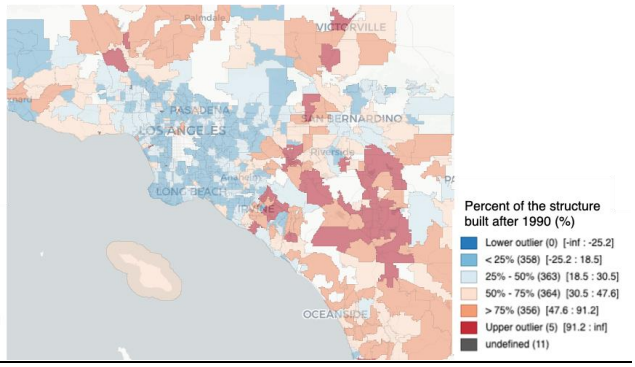
It was found that general high participation coincides with areas that have more recently built homes. In the San Francisco and the peninsula area, the program activity rate is lower (see Figure 5.a). This coincides with our findings that within that area the homes were built prior to 1990 (see Figure 5.b.). In line with this finding, we also noticed that in the East Bay area (i.e. Solano County and Contra Costa County) the participation is higher, which also coincides with our finding that the majority of the homes within these areas were also built after 1990. The trend captured is that the areas with higher participation are those that have homes built after 1990.

Figure 6 Comparison of L.A. Metro Area Program Participation Map & Age of Residence Map

a.



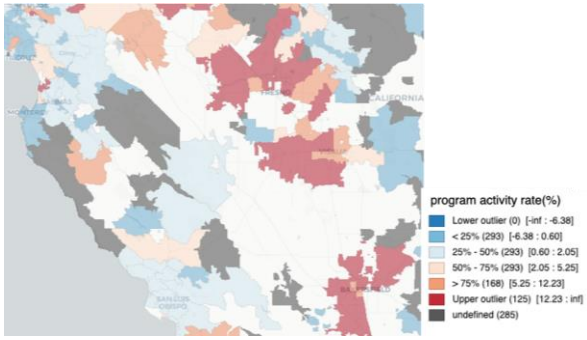
b.



Our findings demonstrate that in the Central L. A. Metro area, where the participation is lower (see Figure 6.a), there is a high percentage of structures built prior to 1990 (see Figure 6.b.). Whereas, areas such as Orange County and other suburban areas which have a high rate of homes built after 1990, demonstrate a high participation rate.

Figure 7 Comparison of San Joaquin Valley Program Participation & Age of Residence Map

a.



b.

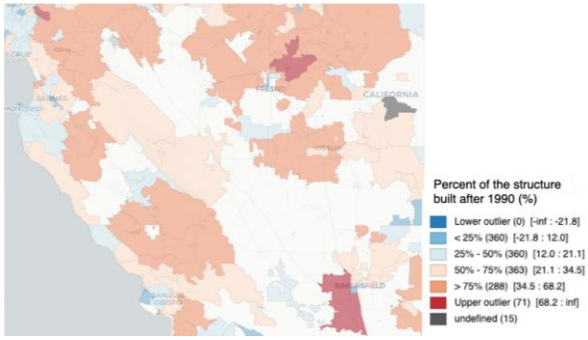
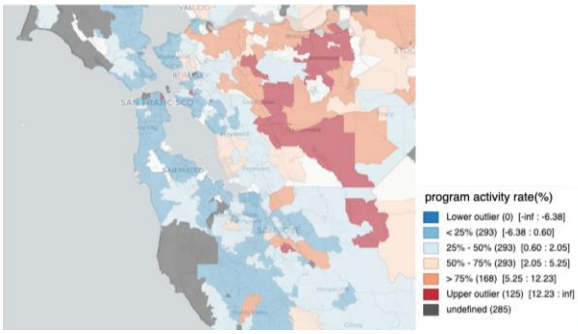


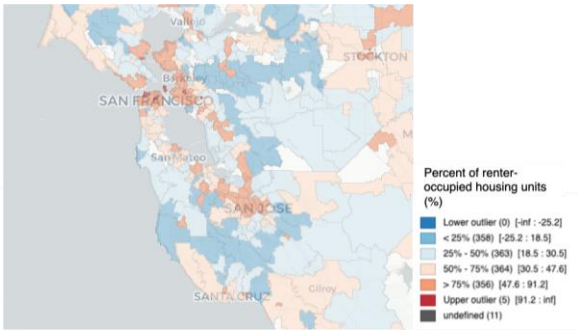
Figure 7.a) shows that in the San Joaquin Valley there is a high participation cluster around Fresno and Bakersfield. The structures in San Joaquin Valley are generally homes built after 1990 (see Figure 7.b.), which also happen to have a high participation rate.

Figure 8 Comparison of Bay Area Program Participation & Renter Occupied Housing

a.



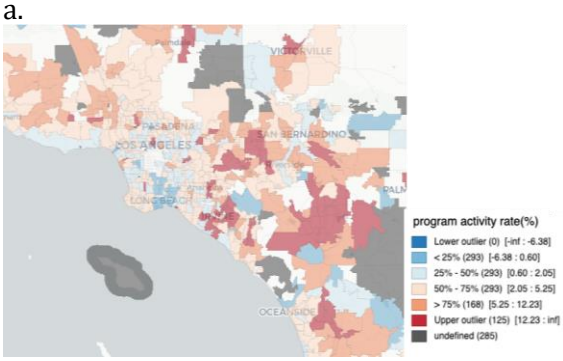
b.



Among zip codes in the Bay Area, areas with low participation coincide with areas showing higher rates of renter-occupied housing units. In Figure 8.a., program activity ranges in the first and second quartile. In comparison, Figure 8.b., greater percentages of renter-occupied housing units are within the third and fourth quartile.

Figure 9 Comparison L.A. Metro Area Program Participation & Renter Occupied Housing Units

a.



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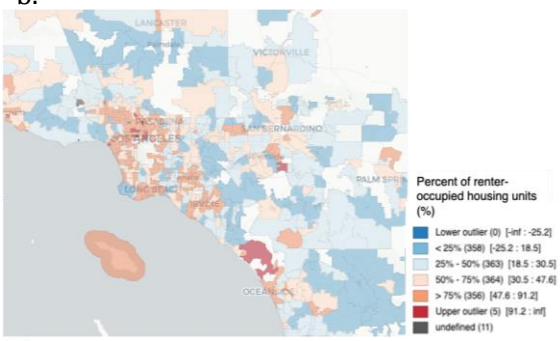
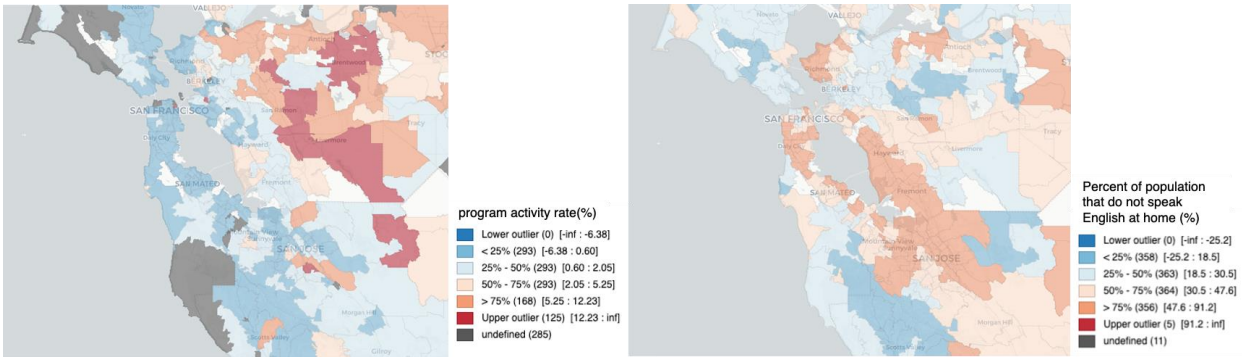


In Figure 9.a., high levels of program participation can be seen in the Greater Los Angeles and Orange County areas, as well as along the coast. Figure 9.b shows zip codes with higher percentages of renter-occupied housing units are concentrated in the Los Angeles metropolitan area. In comparison, low program activity seems to be conversely related to high renter-occupied housing units. Participation and renter occupied housing unit trends in the GLA are similar to those observed in the Bay Area.

Figure 10 Comparison of Bay Area Program Participation & Language at Home Not English

a. b.



In Figure 10.a, lower program participation can be observed in the areas adjacent to the San Francisco Bay. Program activity levels in these areas are among the first and second quartile. At the same time, the higher program activity is seen to occur more inland, in Livermoore and east of San Jose. In comparison, Figure 10.b zip codes with a higher percentage of people who do not speak English at home are in the third and fourth quantiles. Compared to Figure 11, the pattern of low participation and a higher percentage of renter-owned housing units is similar.

Figure 11 Comparison of L.A. Metro Area Program Activity & Language at Home is not English

a. b.

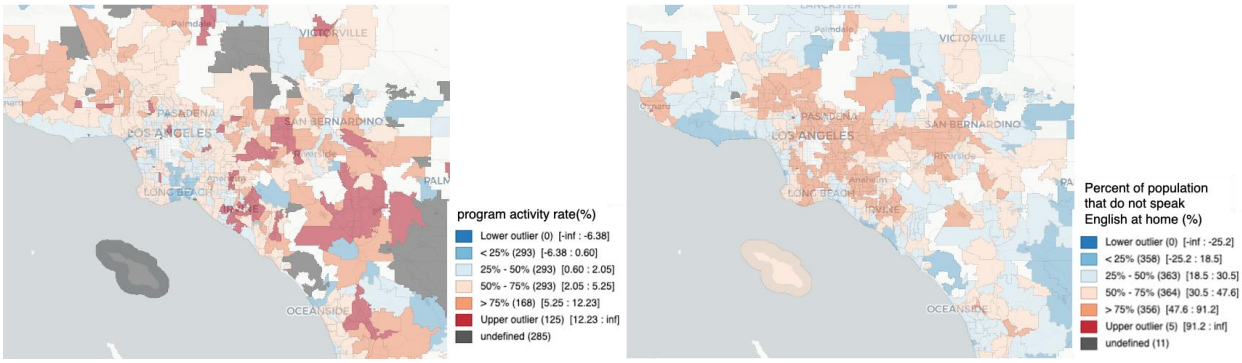


Figure 11 compares program activity and areas with a high percentage of zip codes where the language at home is not English. In Los Angeles City, program activity levels are within the first through third quartile and indicate lower participation levels compared to neighboring areas. Among much of the same regions of Figure 11.b, a higher percentage of households where the language at home is not English participation can be observed. When comparing it to the population that does not speak English at the home map in the same line, we found that areas with low participation tend to overlap/ coincide with a high percentage of the population that does not speak English at home.

ANALYSIS OF SOCIO DEMOGRAPHIC CHARACTERISTICS

Further examination of socio demographic characteristics among zip codes with activity levels between -6.37 and 12.22 reinforced trends observed among our geographic visualizations. When comparing program activity among all participants, analysis revealed that income level, while it can be a limiting factor, was found not to have a significant impact on program activity. The following comparisons identify significant relationships among participants based on rural/urban, language, place of birth, ethnic majorities, and household type.

RURAL / URBAN COMPARISON

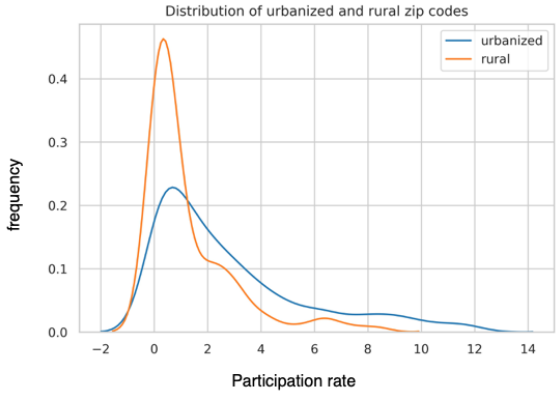
Consistent with our hypothesis, zip codes in urbanized areas have a significantly higher participation rate than those located in rural areas. The Census Bureau classifies those with a population of less than 2,500 as rural. In contrast, communities of 2,500 or more identify as urban zip codes (see Table 6). There are 378 rural zip codes in the non-low-income areas initially, and 109 zip codes remain after removing outliers.

Table 6 Average Program Activity per Household of Rural and Urbanized Zip Codes

	Population Size	**Average Program Activity per Household**
Rural	<2500	2.97
Urban	≥ 2500	5.00

(Source: ACS, 2018; CEDARS, 2019)

Figure 12 Distribution of Program Activity per Household of Rural & Urban Zip code



(Source: ACS, 2018; CEDARS, 2019)

The difference between the average program activity rate of urbanized zip codes and rural zip codes is 2.03. When a T-test was run of the difference between the urbanized and rural zip codes, we found the T-test value to be 8.14, and P value is 0.02 (<0.05). Meaning that the difference of program activity rate between the rural and urban areas is statistically significant at 95% interval. Consistent with geographic observations regarding rural and urban areas, as the homogeneity of zip codes rise, the participation level falls.

HOME LANGUAGE COMPARISON

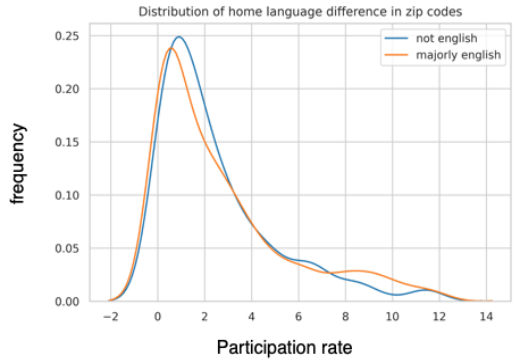
Table 7 Program Activity Among Zip Code Home Language

Population > 50%	Average Program Activity
Home language not English	2.48
Home language is English	2.69

(Source: ACS, 2018; CEDARS, 2019)

The difference between the average program activity rate of zip codes with home language being English vs. not is 0.21. In the T-test the difference between the average program activity rate of zip codes with a population majority whose home language is English v. not English, P value is 0.13 (>0.05), meaning there is no significant difference of program activity rate between the two majority groups.

Figure 13 Distribution of Program Activity per Household of Spoken English



(Source: ACS, 2018; CEDARS, 2019)

Zip codes with the highest percentages of population whose home language is English have no significant difference with those whose home language is not English on average program activity rate (see Figure 13).

NATIVE/FOREIGN-BORN COMPARISON

Table 8 Program Activity Among Zip Codes with Native- & Foreign-Born Population

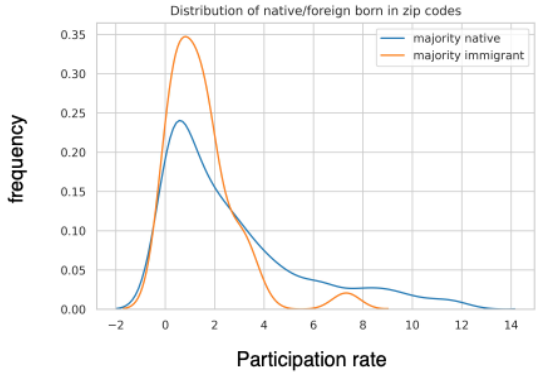
Population > 50%	Average Program Activity
Native born	2.70
Foreign born	1.46

(Source: ACS, 2018; CEDARS, 2019)

The difference between the average program activity rate of zip codes with native-born majority and foreign-born majority is 1.24. In the T-test of the difference, P value is 0.00 (<0.01), which

means that there is a significant difference of program activity rate between the two majority groups at 99% interval. In Figure 22, we can conclude that compared to native-born population, Zip Codes with a majority of foreign born are participating significantly less.

Figure 14 Distribution of Program Activity per Household of Native & Foreign Born



(Source: ACS, 2018; CEDARS, 2019)

ETHNIC GROUP COMPARISON

We compared different race majority zip codes to find if energy efficiency programs are benefiting different racial groups equally. We defined ethnic majority as percent of the ethnic group in one zip code is above 50%.

The difference between the average program activity rate of zip codes with white majority and Zip codes with black or African American majority is 1.12 (see Table 9). When we run a T-test of the difference between the white and Black/African American majority zip codes, we find the t-value of T-test is 2.46, and P value is 0.03 (<0.05), which means that the difference of program activity rate between the two ethnic majority groups is statistically significant at 95% interval.

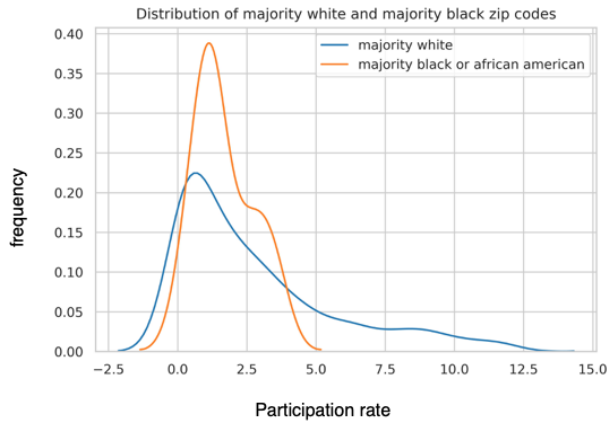
Table 9 Program Activity Among zip codes with White and Black/African American Majority

Population > 50%	**Average Program Activity**
White	2.79
Black/African American	1.67

(Source: ACS, 2018; CEDARS, 2019)

Zip codes with the highest percentages of Black or African American population were more prone to zero program activity (see Figure 15); when compared to zip codes with the highest populations of non-Hispanic white populations.

Figure 15 Distribution of Program Activity per Household of White & Black/African American Majority zip codes



(Source: ACS, 2018; CEDARS, 2019)

In the T-test of the difference between the average program activity rate of zip codes with white majority and zip codes with Hispanic or Latino majority, the t-value is -0.04, and P value is 0.48 (>0.05), which means that the difference of program activity rate between the two ethnic majority groups is not statistically significant (see Table 10).

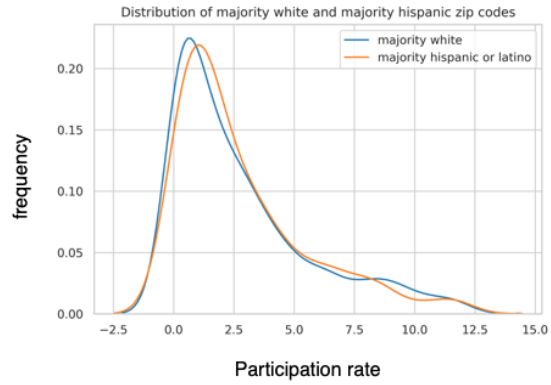
Table 10 Program Activity Among Zip Codes with White and Latino Majority

Population > 50%	Average Program Activity
White	2.78
Hispanic/Latino	2.79

(Source: ACS, 2018; CEDARS, 2019)

Zip codes with the highest percentages of Hispanic or Latino population have no significant difference with the highest populations of non-Hispanic white populations (see Figure 16).

Figure 16 Distribution of Program Activity per Household of White & Hispanic/Latino Majority Zip Codes



(Source: ACS, 2018; CEDARS, 2019)

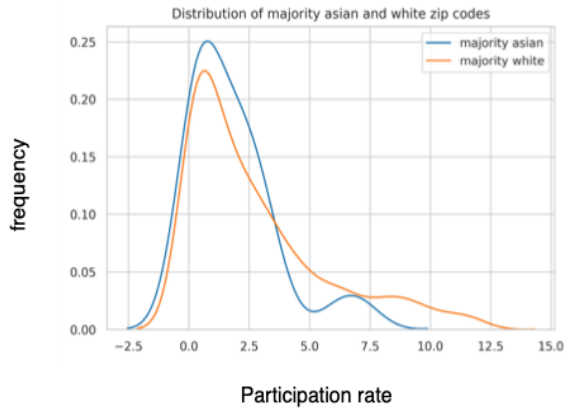
The difference between the average program activity rate of zip codes with white majority and Zip codes with Asian majority is 1.01 (see Table 11). In the T-test of the difference between the average program activity rate of zip codes with white majority and zip codes with Asian majority, P value is 0.00 (<0.01), which means that the difference of program activity rate between the two ethnic majority groups is statistically significant at 99% interval.

Table 11 Program Activity Among Zip codes with White / Asian Majority

Population > 50%	Average Program Activity
White	2.79
Asian	1.78

(Source: ACS, 2018; CEDARS, 2019)

Figure 17 Distribution of Program Activity per Household of White and Asian Majority zip codes



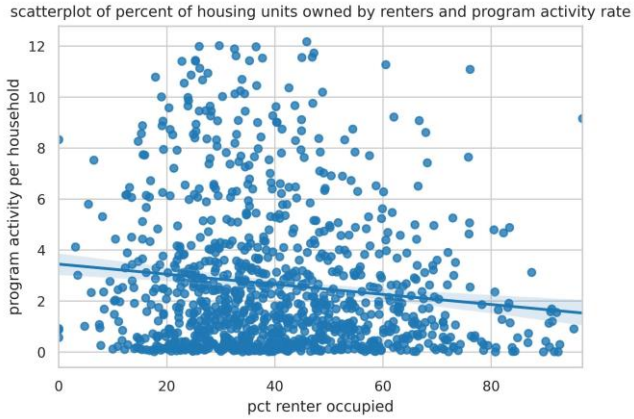
(Source: ACS, 2018; CEDARS, 2019)

Figure 17 shows how zip codes with the highest percentages of Asian population, were more prone to zero program activity when compared to zip codes with the highest populations of non-Hispanic white populations.

RENTER/ OWNER -OCCUPIED COMPARISON

Compared to zip codes where housing units are majority owner-occupied and rental properties participating less.

Figure 18 Scatter Plot of Program Activity per Household and Percent of Households with Majority Renter Occupied



(Source: ACS, 2018; CEDARS, 2019)

In Figure 18, program activity per household and percent of households occupied by renters, the regression relation coefficient is -0.02, the R square is 0.016, which means the model can explain 1.6% of the change. P value is 0.00 (<0.01), the regression relation is significant. Although the regression model cannot explain much of the relationship, we can still find that the higher percentage of housing units occupied by renters, the lower the program activity rate is.

Table 12 Program Activity Among Renter/Owner-Occupied Majority Among Zip Codes

Population > 50%	Average Program Activity
Renter-occupied	2.08
Owner-occupied	2.85

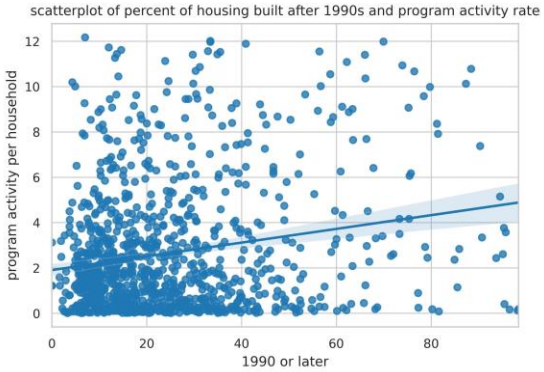
(Source: ACS, 2018; CEDARS, 2019)

In the T-test of the difference between the average program activity rate of zip codes with renter-occupied majority and zip codes with owner-occupied majority, the T-value is -4.06, and P value is 0.00 (<0.01), which means that the difference of program activity rate between the two occupying majority groups is statistically significant. Rental properties are less efficient and less participating than owner-occupied homes.

AGE OF HOMES COMPARISON

The more structures are built after the 1990s (the more modern the zip code is), the higher the participation rate. In Figure 20, the plot graph of program activity per household and percent of households that is 1990 and older is shown in a regression relation coefficient is 0.03, the R square is 0.039, which means the model can explain 3.9% of the change.

Figure 19 Scatter Plot of Program Activity per Household & Percent of Households with Majority built >1990



(Source: ACS, 2018; CEDARS, 2019

P value is 0.00 (<0.01), the regression relation is significant. Although the regression model cannot explain much of the relationship, we can also find that the higher percentage of newer households, the higher the program activity rate is.

IV. CONCLUSION

This research study attempts to determine whether participation gaps by socio-demographic and geographic groups exist in residential energy efficiency programs funded by California's major investor-owned utilities. Our original hypothesis stated that program benefits are not equitably distributed and may not be reaching hard-to-reach customers like lower-income residents, those who do not speak English as their primary language, and those residing in rural areas. Additionally, we anticipated that customers with a higher income level and who reside in more metropolitan areas will show higher participation, investment, and energy savings as compared to customers in harder-to-reach-locations.

For this study's purpose, we analyzed participation data for all residential EE programs administered for customers who reside within the jurisdiction of the California Public Utilities Committee and are not in a disadvantaged community. Preliminary findings indicate that geographic and socio-demographic factors may impact EE program participation as initially hypothesized. Significant differences were observed among different socio demographic groups. In terms of participation gaps, program activity was the lowest among Black / African American households followed by Asian households. However, contrary to the basis for the original hypothesis, it was found that all non-low-income levels participate in EE programs.

We also found that language was not initially a significant factor among participants. When comparing program activity among zip codes based on home language. Analysis showed that participants whose home language was not English participated slightly less than those whose home language is English. However, when we applied further analysis to groups based on place of birth, we found that participants who were born in the United States had a significantly higher rate of participation than those who were born in another country. This would suggest that social

capital or access to resources may be a significant factor, possibly among predominantly immigrant communities.

Spatial analysis of participation data across non-low-income zip codes highlighted higher concentrations of program activity throughout Central and Southern California. Analysis of program activity based on population size supports the hypothesis that customers residing in rural areas are underserved. Rural zip codes showed significantly less program activity when compared to urbanized zip codes.

LIMITS

This study should be considered preliminary as it has several limits. First, the scope of the study included only zip codes that are within the service territory for the state's four IOUs. A full picture of California's participation gap would include areas outside of the IOUs' service territory. Current data from CEDAR does not include the exact number of participants for each program and this limits our ability to directly measure the participation rate among specific programs or delivery models. The provided hotspot analysis identified clusters where program activity rate was highest and lowest. Given that many zip codes are either missing program activity data or Census tract data, the hotspot may not be truly representative of the spatial relationships between participant groups.

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