Impact of Energy Savings Assistance Programs on Monetary Outcomes for Low-Income Households in California

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Abstract

Low-income households encounter challenges affording energy because a significant portion of their income is allocated to cover home energy expenses, resulting in a "high energy burden." Utility companies and government agencies offer assistance programs to ease this financial burden and reduce usage and energy costs. This study delves into the effects of energy assistance programs on the financial well-being of low-income households in California. Specifically, it examines household characteristics and the relationship between participation in these programs and energy affordability. Utilizing the 2020 Residential Energy Consumption Survey (RECS) survey and the Low Income Home Energy Assistance Program (LIHEAP) Data Warehouse, our research employs linear and multiple regression models to analyze the relationship among energy assistance, annual household income, and household characteristics. Such characteristics include the frequency of reducing or forgoing necessities due to home energy bills, employment status, householder race, and the number of household members. The objective is to accurately capture and understand key drivers of high energy burdens so policymakers can effectively identify vulnerable populations needing energy assistance programs. The research findings reveal households participating in these programs experienced a reduction in energy expenses compared to non-participants, indicating a meaningful connection between energy assistance, income level, employment, and other household characteristics. Moreover, our multiple regression analysis revealed that the frequency of forgoing basic necessities due to home energy bills and annual household income in the "very low-income" category emerged as statistically significant predictors for receiving energy assistance programs. The multicollinearity test also revealed a significant association between "very low-income" and "energy assistance."

1. Introduction

With rising electricity prices and climate change concerns, this study explores the efficacy of utility bill assistance programs in alleviating high energy burdens for economically vulnerable Californian households. Energy inequality examines disparities in access, affordability, and attainability of adequate and sustainable energy between socioeconomic groups. Literature on energy inequality emphasizes that low-income groups face difficulties, as they spend a disproportionate share of income on home energy costs, leading to difficult trade-offs with basic necessities. Recent statistics from Energy.gov reveal the national average energy burden for low-income groups is 8.6 percent of income, exceeding the six percent threshold for high burdens. Despite efforts, their energy burden persists and remains high in specific geographies, including the South, rural America, and minority communities. This persistence is crucial in understanding the broader issue of energy poverty, where low-income households struggle to afford basic electricity and heating needs.

To illustrate this, Brown et al. highlight that low-income families experience constraints in adopting innovative energy efficiency technologies and distributed generation systems due to limited financial resources. Consequently, the worsening affordability issues due to increasing home energy bill prices raise great concern, especially for households served by Pacific Gas & Electric Co., which are projected to pay approximately 384 dollars more in 2024 to meet rising demands for electricity. Placing this matter within the discussion of alleviating economic hardship through policy support, we will investigate the potential transformative impact of Energy Savings Assistance Programs (ESAPs). These programs offer bill payment assistance and energy-efficient appliance upgrades for income-qualified households managed by utility companies and public agencies. With funding provided by the California Public Utility Commission (CPUC) amounting to the 358 million budget from 2022 to 2026, ESAPs, established in 2001, aim to address energy poverty by covering expenses for high-efficiency appliance replacements in low-income homes. Descriptive evidence (*Figure 1*) reveals the Low Income Energy Assistance Program (LIHEAP), which provides bill subsidies based on high energy cost burdens, has successfully reduced household expenses. We aim to assess whether similar savings can be achieved through California ESAPs, ultimately lowering high energy burdens for eligible households.

Key findings show LIHEAP participation significantly decreased energy cost burdens for low-income households, revealing a robust link emerges between program enrollment and financial relief. The most influential predictors of high energy burdens are very low income and frequently forgoing basic necessities due to home energy bills. However, statistically insignificant interactions between factors suggest that unobserved elements like housing and appliances could affect affordability. While income and hardship frequency effectively target needy groups, the complex nature of energy poverty necessitates further exploration to optimize policy strategies.

2. Background

This study provides valuable state-level insights and a comprehensive perspective on the benefits of low-income households participating in ESAPs. Although prior research touches on the link between assistance and financial security, it lacks the targeted focus provided in this analysis. York et al. (2015) highlight direct benefits for most participating customers, such as discounted products (residential energy-efficient lighting and appliances) and long-term retrofit projects. In addition, Scheidler (2011) underscores the enduring advantages of ongoing energy efficiency policies and program improvements amid rising fossil-based generation costs. Household characteristics, identified as key drivers of energy poverty by Agbim et al. (2020), call attention to the need for policymakers to consider diverse metrics when targeting aid to vulnerable households experiencing high energy burdens. Pigman et al. (2021) contribute valuable context for examining equity in program participation, while Brown et al. (2020) reveal diverse consumption patterns. Their findings indicate that low-income residents in minority neighborhoods experience a 1.56 percent higher energy burden compared to those in predominantly non-Hispanic white communities.

This research analyzes the relationship between ESAP participation and its impact on energy burdens while evaluating associated employment status, health, demographics, and income constraints impacting energy affordability. We quantitatively analyze these connections to provide evidence that can shape provision policies and optimize social welfare gains. Furthermore, we aim to identify which characteristics are significant predictors for energy assistance, thus helping policymakers identify potential households requiring aid more effectively. Positioned within discussions on an equitable transition to sustainable energy systems, we seek to inform policies targeting low-income households, contributing more to effective and targeted interventions in energy poverty.

We employed linear probability models in the initial analysis stage to examine the correlation between energy assistance and household income. Subsequently, in the second stage, we transformed variables into binary and factor types, enabling us to segment the sample and conduct subgroup analyses. This involved exploring the relationship between assistance participation and income across diverse demographic groups to unveil nuanced variations within distinct subgroups. We also ran a multicollinearity test and looked for interaction effects.

3. Methods

3.1 Data

Our research is built on the foundation of microdata from the 2020 Residential Energy Consumption Survey (RECS), which collects information on household-level energy usage, expenditures, and related socioeconomic factors from thousands of households nationwide. Conducted periodically by the Energy Information Administration since 1978, this survey employs a random sample approach, ensuring coverage across all types of housing units and providing a comprehensive overview of residential energy trends in the United States.

Drawing upon this framework, we focus our analysis specifically on responses exclusively from the state of California. This targeted approach yields a dataset consisting of 1,136 observations across 17 distinct variables, encompassing information such as annual energy expenditures, household income, householder race, employment status, and household size, and critically for our investigation, whether the household received energy assistance in 2020 and the frequency of energy-related financial hardships.
The diversity of economic and demographic traits captured by the RECS data enables us to model household characteristics associated with a higher likelihood of benefitting from affordability programs. These programs are intended to ease energy cost burdens for vulnerable groups, making our research instrumental in understanding and addressing challenges related to energy affordability.

In our study, the key explanatory variable is annual household income, and we are investigating its impact on predicting the likelihood of a household requiring energy assistance. Within our dataset, the variable '*moneypy*' is a proxy for annual household income, encompassing factor values ranging from 1 to 16. These values correspond to a broad income spectrum, spanning from less than $5,000 to $150,000 or more. To better understand the income distribution, we categorized households based on their '*moneypy*' values. Response codes 1 to 10 classify households as "Very Low-Income," denoting an income range from less than $5,000 to $39,999. Response codes 11 to 13 represent the "Low-Income" category, indicating an income range of $40,000 to $74,999. Lastly, response codes 14 to 16 designate the "Median and Above Income" category, encompassing households earning $75,000 to $150,000 and beyond. We opted to combine median household income and incomes surpassing the median threshold to streamline income groups, allowing us to concentrate on low-income brackets, which are the focal point of our research.
The income classifications we employed are based on California's 'State Income Limits for 2020.' Considering the median household income in the dataset is $87,100, we established the "Median and

Above Income" category to mirror the lower boundary of that median value, aligning it with the nearest approximate income range. The "Low-Income" category, at eighty percent of the median income, approximates $69,680. Accordingly, we assigned this category at the upper limit of the median value, aligning it with the closest approximate income range. The "Very Low-Income" category, equivalent to fifty percent of the median income or approximately $43,550, was placed at the upper limit of this income range. While our income categories may not precisely mirror state income limits, these estimations serve the purpose of our analysis, as elucidated in later sections of this research.

The key outcome variable centers around whether households have received energy assistance and explores independent variables to predict the likelihood of a household seeking such assistance. Our dataset's binary variable 'energyasst_dummy' represents whether energy assistance has been received. It takes on a value of 1 if assistance has been received and 0 if not. This variable, derived from the Residential Energy Consumption Survey (RECS), forms the basis for our analysis.

Beyond energy assistance, we incorporate additional household variables to enrich our analysis. The variable '*employhh_dummy*' reflects employment status and is a binary variable. By combining codes 1 and 2 (representing 'Employed full-time' and 'employed part-time'), we assign a value of 1 to indicate employment and combine codes 3 and 4 (representing 'Retired' and 'Not employed') with a value of 0 to signify unemployment. The '*householder_race*' variable, representing the racial background of the householder, is a factor variable. We streamline multiple racial categories into broader identifications, choosing response codes 1, 2, and 4 to represent 'White Alone,' 'Black or African American Alone,' and 'Asian Alone,' respectively.

The '*nhsldmem*' variable denotes the number of household members and is a numeric variable, with each response code from 1 to 7 corresponding to the number of household members.
Considering the impact of home energy bills on basic necessities, we introduce the '*scaleb_dummy*' variable. This binary variable is created by merging codes 1, 2, and 3 (representing 'Almost every month,' 'Some months,' and '1 or 2 months'), assigning a value of 1 to indicate instances where individuals have forgone basic necessities, and 0 for cases where this has not occurred. This consolidation aims to capture a meaningful affirmative response, given the temporal nuances among the initial response codes.
This combination of indicators encapsulating economic resources, livelihood stability, household dependencies, and expense tradeoff behaviors provides sufficient data from over a thousand California homes to thoroughly model household characteristics associated with a higher likelihood of benefiting from aid programs working to ease energy cost burdens.

Descriptive output for key variables:

Table 1 provides an overview of key statistics, including minimum, maximum, and median values, for the pivotal explanatory, outcome, and household variables derived from the RECS. **Table 2** delves into the linear regression model outcomes, specifically examining the relationship between home energy assistance and annual household income within the distinct categories of "Very Low-Income" and "Median and Above Income." Remarkably, our analysis reveals a statistically significant positive relationship at the one percent level between home energy assistance and very low household income, alongside a statistically significant negative relationship at the five percent level between home energy assistance and median and above household income.

Moving to **Table 3**, we extend our exploration through a multiple regression model, considering not only home energy assistance (*'energyasst_dummy*') and annual household income ('*moneypy*') but also the frequency of reducing or forgoing basic necessities due to home energy bills ('*scaleb_dummy*'). Notably, a statistically significant positive relationship at the one percent level persists between home energy assistance and very low household income. Additionally, we unveil a significant positive relationship at the one percent level between home energy assistance and the frequency of frequently forgoing basic necessities due to home energy bills.

Table 4 expands our analysis further by introducing employment status ('*employhh_dummy*') into the multiple regression model, building upon the variables explored in Table 3. Remarkably, the two significant findings from Table 3 regarding the positive relationships between home energy assistance and very low household income, as well as the frequency of forgoing basic necessities, persist in this extended model, with coefficients remaining unchanged. These empirical insights contribute valuable nuances to the economic research landscape, shedding light on the intricate dynamics between household income, energy assistance, and associated factors.

In Table 5, we extend our multiple regression model to encompass a broader array of variables, incorporating home energy assistance ('*energyasst_dummy*'), annual household income ('*moneypy*'), the frequency of reducing or forgoing necessities due to home energy bills ('*scaleb_dummy*'), employment status ('*employhh_dummy*'), the number of household members ('*nhsldmem*'), and householder race ('*householder_race*'). The two significant findings from Table 3 persist in this comprehensive model, with coefficients experiencing an increase of approximately half a percentage point. Additionally, a new noteworthy finding emerges, indicating a statistically significant positive relationship between home energy assistance and the number of household members at the ten percent level. Furthermore, we identify a statistically significant negative relationship at the ten percent level between home energy assistance and Asian householders.

In **Table 6**, we conducted a multicollinearity test to assess the relationship among predictor variables, including annual household income (‘*moneypy*’), frequency of forgoing basic necessities due to home energy bills (‘*scaleb_dummy*’), employment status (‘*employhh_dummy*’), number of household members (‘*nhsldmem*’), and householder race (‘*householder_race*’). Examining Generalized Variance Inflation Factor (GVIF) values reveals that all are close to 1. This proximity to 1 indicates low multicollinearity among the predictor variables. Therefore, in our model, the variables exhibit minimal correlation, affirming that including these predictors does not introduce issues related to multicollinearity. This observation enhances the robustness of our model, ensuring that each predictor contributes independently to the understanding of the relationship between home energy assistance and the examined household characteristics.

In **Figure 1**, a bar graph compares average annual household energy burdens before and after implementing the Low-Income Home Energy Assistance Program (LIHEAP). A significant trend emerges across all fuel categories, indicating a notable decrease in the average annual household energy burden due to LIHEAP. This finding underscores the program's effectiveness in alleviating the energy-related financial strain on households across various income levels.

Figure 2 is a bar graph portraying the relationship between household income and total energy usage, represented on a logarithmic scale sourced from the RECS. An important trend is discerned, revealing that energy consumption increases with income. Specifically, the highest-income households, earning $150,000 or more, exhibit the highest energy consumption levels. This insight sheds light on the correlation between income and energy usage patterns, emphasizing the potential implications for energy policy and resource allocation based on household income levels. Both figures contribute valuable information to the broader understanding of the dynamics between energy assistance, household income, and energy consumption.

The structure of our working dataset is organized such that each row represents household information from California residents, specifically in the year 2020. The main focus is investigating whether factors beyond annual income are key drivers of energy poverty, providing insights into indicators to help identify households needing energy assistance. By examining various household characteristics, we aim to discern patterns and relationships contributing to a comprehensive understanding of California’s energy poverty dynamics. This approach enables us to explore the multifaceted nature of the factors influencing the energy needs of households. It goes beyond a singular focus on annual income, enriching our analysis and contributing to a more nuanced perspective on energy assistance requirements.

3.2 Empirical Strategy

We focus our analysis on California for two key reasons. First, the state's large population and high energy costs, in contrast to national averages, underscore its significance in assessing the effectiveness of existing aid programs in reducing energy burdens. With over one in three California households qualifying as low-income, they struggle disproportionately to afford the state's increasingly high electricity bills driven by renewable investments and wildfire mitigation charges. Secondly, California's long-running assistance efforts, like the California Alternate Rates for Energy (CARE) program, provide monthly discounts on utility bills for eligible low-income households and housing facilities that provide historical participation data supporting rigorous impact analysis.

Therefore, our study aims to quantitatively assess whether participation in energy savings assistance programs among low-income households in California positively influences the ability to afford energy bills and, therefore, reduce energy poverty. Specifically, we seek to scrutinize multivariate correlations and statistical significance to understand the connection between enrolling in utility bill discounts, financial aid initiatives, and improved monetary outcomes related to energy costs and household budgets.

We utilized a linear probability model for the first stage analysis detailed in Tables 2, 3, 4, and 5. This model evaluated the relationship between the likelihood of receiving home energy assistance, represented by the variable '*energyasst_dummy*,' and the annual household income of the previous year. Income was categorized into "Very Low-Income," "Low-Income," and "Median and Above Income"" groups using the factor variable '*moneypy*.' The low-income group served as the reference category in our models when setting other variables equal to 0. This analysis assessed whether lower earnings predict a higher probability of enrolling in energy assistance programs to alleviate energy burdens.

In the second analysis stage, we adopted a stepwise approach, incrementally introducing additional explanatory variables related to employment status, energy hardship, and demographics. We incorporated a binary indicator, '*employhh_dummy,*' to denote whether the householder was employed or unemployed. We accounted for experiences of energy needs tradeoffs using the variable '*scaleb_dummy*,' indicating the frequency of reducing or forgoing basic necessities like food, medicine, or heat to afford energy bills. Additionally, we introduced the number of household members variable, '*nhsldmem*,' and controlled for race using the categorical factor variable '*householder_race*.' Transforming these household variables into dummy and factor formats facilitated smoother inclusion into our probability models containing multiple levels. Analyzing how the income relationship evolves with the addition of each characteristic sheds light on the relative importance and connections between income, employment, frequency of economic hardship, race, and obtaining energy affordability assistance.

The equations for the model are as follows:

- Model 1: $energyasst\_dummy_i = \beta_0 + \beta_1 \cdot moneypy_i + \varepsilon_i$
- Model 2: $energyasst\_dummy_i = \beta_0 + \beta_1 \cdot moneypy_i + \beta_2 \cdot scaleb\_dummy_i + \varepsilon_i$
- Model 3: $energyasst\_dummy_i = \beta_0 + \beta_1 \cdot moneypy_i + \beta_2 \cdot scaleb\_dummy_i + \beta_3 employhh\_dummy_i + \varepsilon_i$
- Model 4: $energyasst\_dummy_i = \beta_0 + \beta_1 \cdot moneypy_i + \beta_2 \cdot scaleb\_dummy_i + \beta_3 employhh\_dummy_i + \beta_4 nhsldmem_i + \varepsilon_i$
- Model 5: $energyasst\_dummy_i = \beta_0 + \beta_1 \cdot moneypy_i + \beta_2 \cdot scaleb\_dummy_i + \beta_3 employhh\_dummy_i + \beta_4 nhsldmem_i + \beta_5 householder\_race_i + \varepsilon_i$

Where:

- $\boldsymbol{energyasst\_dummy_i}$ = represents the energy assistance for the i^{th} household.
- $\boldsymbol{moneypy_i}$ = represents annual gross household income for the past year for the i^{th} household.
- $\boldsymbol{scaleb\_dummy_i}$ = represents frequency of reducing or forgoing basic necessities due to home energy bills i^{th} household.
- $\boldsymbol{employhh\_dummy_i}$ = represents the respondent's employment status for the i^{th} household.
- $\boldsymbol{nhsldmem_i}$ = represents the number of household members for the i^{th} household.
- $\boldsymbol{householder\_race_i}$ = represents the householder (respondent) race for the i^{th} household.

The coefficients β1 through β5 capture the correlation between each independent variable and the likelihood of obtaining energy assistance, with 'β0' representing the constant term. The error term 'εi' is the error term.

To ensure the appropriateness of incorporating multiple explanatory variables, we conducted a thorough collinearity assessment by running a multicollinearity test. Specifically, we examined the Generalized Variance Inflation Factor (GVIF) values for each predictor in our model. Elevated GVIF values, significantly surpassing 1, indicate high correlations between the independent variables, potentially undermining the interpretation of coefficient estimates outlined in Table 6. Additionally, we conducted an interaction test among our explanatory variables to evaluate whether the combined impact of household characteristics provides a more comprehensive explanation for variations in receiving energy assistance ('*energyasst_dummy*') beyond individual predictors. However, given the lack of statistical significance in these interactions, we excluded them from further consideration.

4. Results

The results from our analysis, as presented in Table 5, reveal significant predictors of energy assistance receipt among California households in 2020. Notably, very low household income emerges as a pivotal factor, with households in this category being 17.5 percent more likely to receive energy assistance, underscoring the substantial impact of low income on predicting the need for energy support. Furthermore, those who frequently forgo necessities due to home energy bills show a 6.1 percent higher likelihood of receiving energy assistance, indicating the interconnected nature of financial struggles and energy assistance needs. These findings are statistically significant at the one percent level.

Less significant predictors, though still relevant, include the number of household members and householder race, each with a ten percent significance level. Specifically, an additional household member increases the likelihood of receiving energy assistance by 1.2 percent, while Asian householders are 4.3 percent less likely to receive energy assistance. Again, we investigated the interaction between Asian householders and income but did not find significant results to suggest why, compared to other races, are least likely to receive energy assistance.

In contrast, certain variables, namely median and above household income, employment status, and Black householders, emerge as statistically insignificant predictors. Median and above income households are 3.1 percent less likely to receive energy assistance, employment decreases the likelihood by 0.7 percent, and Black householders are 0.8 percent less likely to receive assistance.

Table 6 provides insights into the robustness of our model, indicating low multicollinearity among explanatory variables and negligible correlation. The only significant interaction identified is between the explanatory variable, ‘*moneypy*Very Low-Income,’ and the dependent variable, ‘*energyasst_dummy*,’ underscoring the detailed relationship between income levels and energy assistance receipt. However, tests for interaction effects between these household characteristics and energy assistance receipt revealed no statistically significant higher-order relationships. Joint impacts did not improve model performance beyond the already captured individual effects. Yet despite lacking multivariate effects, the single variable ‘*moneypy*’ in the “Very Low-Income” income category emerges as highly significant ($p < 0.01$) in predicting aid reliance. Furthermore, the regression overall signifies at least one meaningful connection, with an F-statistic confirming joint explanatory capacity. The adjusted R-squared value of 0.116 conveys predictors account for over 11 percent of the variation in assistance participation. So, while boosting sophistication through interactions proved unnecessary, the analysis still provides a practical starting point for policy targeting based primarily on income level.

As reflected in R-squared values ranging from 10.1 to 11.2 percent, the models explain a modest yet noteworthy proportion of the variation in energy assistance receipt. Furthermore, our analysis indicates a statistically significant correlation between participation in utility bill payment assistance programs and improved energy affordability outcomes, such as reduced costs and lower financial hardship. These findings contribute valuable insights to economic research, informing policymakers and stakeholders about the multifaceted determinants of energy assistance needs and potential avenues for intervention.

5. Conclusion

This analysis contributes valuable insights to the existing research on the impacts of energy assistance programs for low-income households. The findings reveal that energy savings assistance programs effectively improve energy affordability among disadvantaged communities by reducing energy burdens. The regression results and descriptive trends confirm that energy assistance receipt is associated with substantially lower energy burdens. Participating households experience burdens of 3-4 percentage points below non-participants, demonstrating meaningful financial protections from existing aid. More generous benefits and expanded eligibility may be needed to relieve energy burdens substantially. Notably, participation in utility bill payment assistance programs exhibits a statistically significant correlation with improved energy affordability outcomes, like reduced costs and lower incidence of hardship. While the improvements are meaningful, they signify partial finance protection, highlighting opportunities to enhance program design. These results contribute empirical evidence on the efficacy of energy aid initiatives in easing cost burdens among vulnerable populations. At the same time, our analysis captures a multidimensional perspective on the various drivers of energy burdens within this demographic. Highlighting the prominence of “very low-income" as the most crucial predictor for energy assistance underscores the imperative role income plays in various aspects. This encompasses the ability to cover energy costs, implement energy-efficient technologies at home, purchase higher-quality and energy-efficient housing, and invest in renewable energy to cut costs. The second most significant predictor, the frequent forgoing of basic necessities due to home energy bills, further emphasizes the link between income constraints and households’ difficult tradeoffs in managing energy expenses.

Limitations stem primarily from the one-year cross-section, which cannot support causal claims or gauge the long-term durability of affordability improvements. Additionally, self-reported survey measures present potential response biases. Follow-up work could leverage panel install-level data and instrumental variable techniques to bolster identification. Relatedly, future research might investigate interactions across race and income or nonlinear program effects as assistance levels increase to sharpen targeting calibration and optimize offerings. But despite constraints, these findings equip policymakers to maximize assistance value through enhanced enrollment facilitation and benefit expansion for compounding low-income groups. Streamlining eligibility requirements, raising awareness in vulnerable communities, and dynamically customizing based on intersecting socioeconomic indicators can better match aid to the level of need. Augmenting current successful initiatives promises substantial relief as California reconciles equity and sustainability ambitions.

Table 1: *RECS variables used for regression analysis and nominal relationship to household patterns and concepts.*

Section	Variable	Response Code	Min	Max	Median
Energy Assistance	Received home energy assistance (energyasst)	1 - yes 0 - No 2 - Not Applicable	0	0	1
Household Characteristic	Annual gross household income for the past year (moneypy)	1 Less than $5,000 2 $5,000 - $7,499 3 $7,500 - $9,999 4 $10,000 - $12,499 5 $12,500 - $14,999 6 $15,000 - $19,999 7 $20,000 - $24,999 8 $25,000 - $29,999 9 $30,000 - $34,999 10 $35,000 - $39,999 11 $40,000 - $49,999 12 $50,000 - $59,999 13 $60,000 - $74,999 14 $75,000 - $99,999 15 $100,000 - $149,999 16 $150,000 or more	1	14	16
Energy Assistance	Frequency of reducing or forgoing basic necessities due to home energy bill (*scaleb*)	1 Almost every month 2 Some months 3 1 or 2 months 0 Never	0	0	3
Household Characteristic	Respondent employment status (*employhh*)	1 Employed full-time 2 Employed part-time 3 Retired 4 Not employed	1	2	4
Household Characteristic	Number of household members (top-coded) (*nhsldmem*)	1-7	1	2	7
Household Characteristic	Householder (respondent) race (*householder_race*)	1 White Alone 2 Black or African/American Alone 3 American Indian or Alaska Native Alone 4 Asian Alone 5 Native Hawaiian or Other Pacific Islander Alone 6 2 or More Races Selected	1	1	6

NOTES: The presented variables are sourced from the RECS (2020). The table presents a detailed overview of multiple variables about energy assistance, household characteristics, and end-use models derived from the dataset. It covers significant aspects such as the receipt of home energy assistance, annual gross household income categories, frequency of reducing or forgoing basic necessities due to energy bills, household members, total energy usage, and the respondent's race. For instance, the data reveals insights about household income distribution, frequencies of energy bill-related adjustments, employment status, household size, and energy usage while capturing the respondent's race. This table comprehensively explains the diverse factors influencing energy assistance and household dynamics. It contributes to a richer comprehension of the interplay between various elements and their implications in energy use and financial assistance programs.

Table 2: *Linear regression model: the relationship between home energy assistance (energyasst_dummy) and annual household income (moneypy).*

	Dependent Variable
	energyasst_dummy
*moneypy*Very Low-Income	0.175*** (0.003)
*moneypy*Median and Above Income	-0.041** (0.021)
Constant	0.063*** (0.017)
Observations	1,136
Adjusted R	0.101

Note: *p<0.1; **p<0.05; ***p<0.01, signifying the levels of statistical significance.

NOTES: The table displays the relationship between receiving home energy assistance, '*energyasst_dummy*,' and the annual gross household income of the previous year, '*moneypy*,' in the "Very Low-Income" and "Median and Above Income"' categories. Note the constant represents our reference category, which is an individual in the "Low-Income" category. It has a coefficient of 0.063 with a significance level of *** ($p < 0.01$), indicating a statistically significant positive association between energy assistance and low-income households. Moreover, it also indicates that low-income households have a 6.3 percent likelihood of receiving energy assistance, while other factors hold constant.

The coefficient for '*moneypy*Very Low-Income' is 0.175 with a significance level of *** ($p < 0.01$), indicating a statistically significant positive association between energy assistance and very low household income. This result suggests that compared to our constant, very low-income households are 17.5 percent more likely to receive energy assistance.

The coefficient for '*moneypy*Median and Above Income' is -0.041 with a significance level of ** ($p < 0.05$), indicating a statistically significant negative association between energy assistance and median and above household income. This result suggests that, compared to our constant median and above-income households, they are 4.1 percent less likely to receive energy assistance.

The observed data include 1,136 cases, and the adjusted R-squared value stands at 0.101, indicating household income can explain roughly 10.1 percent of the variation in energy assistance.

Table 3: *Multiple regression model: the relationship between home energy assistance (energyasst_dummy), annual household income (moneypy), and the frequency of reducing or forgoing basic necessities due to home energy bills (scaleb_dummy).*

	Dependent Variable	
	energyasst_dummy	
	(1)	(2)
*moneypy*Very Low-Income	0.175*** (0.023)	0.163*** (0.023)
*moneypy*Median and Above Income	-0.041** (0.021)	-0.033 (0.021)
scaleb_dummy		0.066*** (0.022)
Constant	0.063*** (0.017)	0.051*** (0.018)
Observations	1,136	1,136
Adjusted R	0.101	0.107

Note: *p<0.1; **p<0.05; ***p<0.01, signifying the levels of statistical significance.

NOTES: For the '*moneypy*Very Low-Income' variable, the coefficient has decreased by 1.2 percent, while the '*moneypy*Median and Above Income' variable has increased by 0.8 percent and is no longer statistically significant. The constant has decreased by 1.2 percent.

The introduction of the '*scaleb_dummy*' variable in this model has a coefficient of 0.66 with a significance level of *** ($p < 0.01$), indicating a statistically significant positive association between the frequency of forgoing basic necessities due to home energy bills and energy assistance. This result suggests that compared to our constant, households that frequently forgo basic necessities are 6.6 percent more likely to receive energy assistance.

The observed data include 1,136 cases for both models, and the adjusted R-squared values stand at 0.101 for '*moneypy*' variables alone and 0.107 when the '*scaleb_dummy*' variable is newly introduced. This result implies approximately 10.1 to 10.7 percent of the variation in energy assistance can be explained by household income and the frequency of forgoing basic necessities due to home energy bills.

Table 4: *Multiple regression model: the relationship between home energy assistance (energyasst_dummy), annual household income (moneypy), the frequency of reducing or forgoing basic necessities due to home energy bills (scaleb_dummy), and employment status (employhh_dummy).*

	Dependent Variable		
	energyasst_dummy		
	(1)	(2)	(3)
*moneypy*Very Low-Income	0.175*** (0.023)	0.163*** (0.023)	0.163*** (0.024)
*moneypy*Median and Above Income	-0.041** (0.021)	-0.033 (0.021)	-0.033 (0.021)
scaleb_dummy		0.066*** (0.022)	0.066*** (0.022)
employhh_dummy			-0.002 (0.017)
Constant	0.063*** (0.017)	0.051*** (0.018)	0.052*** (0.020)
Observations	1,136	1,136	1,136
Adjusted R	0.101	0.107	0.106

Note: *p<0.1; **p<0.05; ***p<0.01, signifying the levels of statistical significance.

***NOTES*:** The '*moneypy*Very Low-Income,' '*moneypy*Median and Above Income,' and '*scaleb_dummy*' variables remain unchanged from the previous interpretation, while the constant has only slightly increased by 0.1 percent. The introduction of the '*employhh_dummy*' variable in this model has a coefficient of -0.002, indicating a negative association between employment status and energy assistance. This result suggests that employed households are 0.2 percent less likely to receive energy assistance than our constant.

The observed data includes 1,136 cases for all models, and the adjusted R-squared values stand at 0.101 for '*moneypy*' variables alone and 0.107 when the '*scaleb_dummy*' variable is introduced, and 0.106 when the '*employhh_dummy*' variable is newly introduced. This result implies approximately 10.1 to 10.6 percent of the variation in energy assistance can be explained by household income, the frequency of forgoing basic necessities due to home energy bills, and employment status.

Table 5: *Multiple regression model: the relationship between home energy assistance (energyasst_dummy), annual household income (moneypy), the frequency of reducing or forgoing basic necessities due to home energy bills (scaleb_dummy), employment status (employhh_dummy), number of household members (nhsldmem), and householder race (householder_race).*

	Dependent Variable				
	energyasst_dummy				
	(1)	(2)	(3)	(4)	(5)
*moneypy*Very Low-Income	0.175*** (0.023)	0.163*** (0.023)	0.163*** (0.024)	0.165*** (0.024)	0.170*** (0.024)
*moneypy*Median and Above Income	-0.041** (0.021)	-0.033 (0.021)	-0.033 (0.021)	-0.037* (0.021)	-0.031 (0.021)
scaleb_dummy		0.66*** (0.022)	0.066*** (0.022)	0.057** (0.023)	0.061*** (0.023)
employhh_dummy			-0.002 (0.017)	-0.006 (0.017)	-0.007 (0.017)
nhsldmem				0.012** (0.006)	0.012* (0.006)
*householder_race*Black or AA					-0.008 (0.032)
*householder_race*Asian					-0.043* (0.023)
Constant	0.063*** (0.017)	0.051*** (0.018)	0.052*** (0.020)	0.025 (0.023)	0.028 (0.024)
Observations	1,136	1,136	1,136	1,136	1,081
Adjusted R	0.101	0.107	0.106	0.109	0.112

Note: *p<0.1; **p<0.05; ***p<0.01, signifying the levels of statistical significance.

N*OTES*: The ‘*moneypy*Very Low-Income’ variable has increased 0.5 percent, the ‘*moneypy*Median and Above Income’ variable has increased 0.6 percent and is no longer statistically significant, and the ‘*employhh_dummy*’ variable has increased 0.1 percent. The constant has increased by 0.3 percent and is no longer statistically significant.

The newly introduced variable, ‘*nhsldmem*,’ has a coefficient of 0.012 with a significance level of * ($p < .10$), indicating a statistically significant positive association between the number of household members and energy assistance. This result suggests that every additional household member increases the likelihood of receiving energy assistance by 1.2 percent compared to our constant.

Another newly introduced variable is '*householder_race,*' segmented into a "Black or African American" and "Asian" category. The '*householder_race*Black or AA' variable has a coefficient of -0.008, indicating a negative association between Black householders and energy assistance. This result suggests that compared to our constant, black householders are 0.8 percent less likely to receive energy assistance. In addition, the '*householder_race*Asian' variable has a coefficient of -0.43 with a significance level of * ($p < .10$), indicating a statistically significant negative association between Asian householders and energy assistance. This result suggests that compared to our constant, Asian householders are 4.3 percent less likely to receive energy assistance.

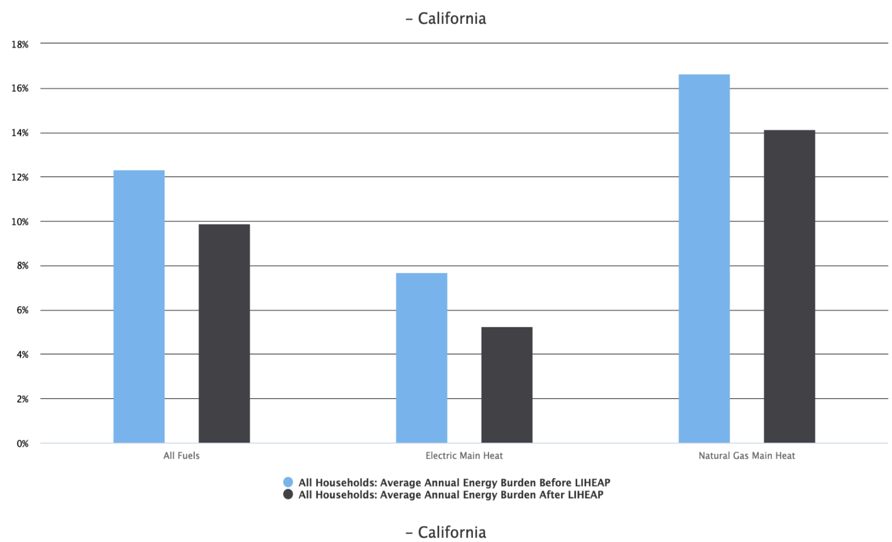
The observed data includes 1,1081 cases for all models, and the adjusted R-squared values stand at 0.101 for '*moneypy*' variables alone and 0.107 when the '*scaleb_dummy*' variable is introduced, and 0.106 when the '*employhh_dummy*' variable is introduced. The values also stand at 0.109 when the '*nhsldmem*' variable is introduced and 0.112 when '*householder_race*' is newly introduced. This result implies approximately 10.1 to 11.2 percent of the variation in energy assistance can be explained by household income, the frequency of forgoing basic necessities due to home energy bills, employment status, number of household members, and race.

Table 6: *Multicollinearity test: the relationship between annual household income, (moneypy), frequency of forgoing basic necessities due to home energy bills (scaleb_dummy), employment status (employhh_dummy), number of household members (nhsldmem), and householder race (householder_race).*

	Multicollinearity		
	GVIF	Df	GVIF^(1/(2*Df))
moneypy	1.25	2	1.06
scaleb_dummy	1.16	1	1.08
employhh_dummy	1.12	1	1.06
nhsldmem	1.10	1	1.05
householder_race	1.06	2	1.01

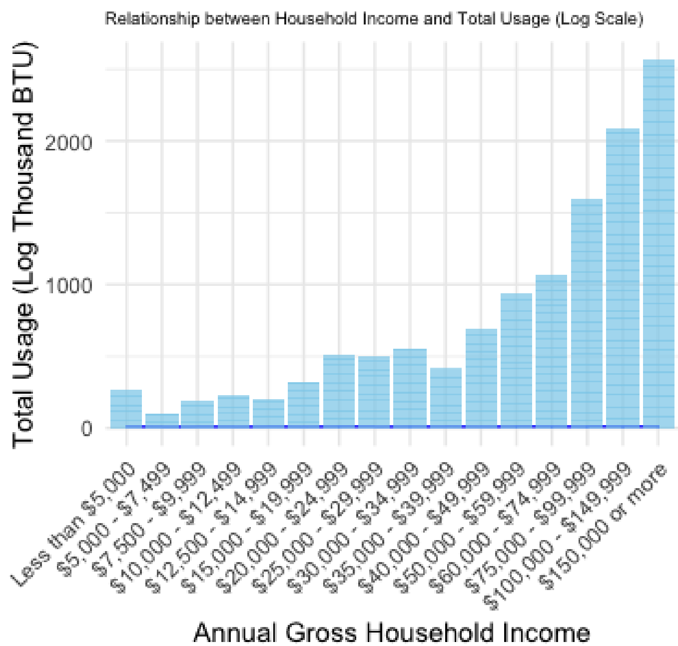
N*OTES:* All Generalized Variance Inflation Factor (GVIF) values are close to 1, indicating low multicollinearity. Therefore, the predictor variables in our model are not highly correlated. We also ran an interactions test to enhance the model's ability to accurately predict our dependent variable, '*energyasst_dummy*,' by accounting for variations that might be missed in a model without interactions. In addition, we wanted to find if a combination of household and demographic factors influenced the probability of receiving energy assistance. Of course, we find the relationship between the '*moneypy*Very Low-Income' variable and the dependent variable, '*eneryasst_dummy*,' statistically significant at the one percent level. Beyond that, all interaction terms have p-values greater than 0.05, indicating these interaction effects are not statistically significant. The relationship between the '*energyasst_dummy*' variable and the interaction of the explanatory variables is not significantly different from the sum of their individual effects. The F-statistic for the overall model is highly significant ($F(26, 1054) = 6.437$, $p < 0.001$), indicating at least one of our predictors is significantly related to the dependent variable, '*energyasst_dummy*,' which would be the '*moneypy*Very Low-Income' variable. Regarding model fit, the adjusted R-squared value of 0.1157 suggests that our model modestly explains approximately 11.57 percent of the variance in the dependent variable, indicating our model provides a meaningful contribution to understanding influential factors.

Figure 1: *Comparison of Pre- and Post-Participation Energy Burden in the Low-Income Home Energy Assistance Program (2020).*



NOTES: Source - Low-Income Home Energy Assistance (LIHEAP) data warehouse. The descriptive bar graph comparison presents a compelling insight indicating a substantial reduction in the energy burden experienced by low-income families before and after their enrollment in LIHEAP. The comparison suggests a noteworthy decline in energy burden levels following participation in the program, signifying a positive impact on energy affordability for households with limited income

Figure 2: *The relationship between household income and total energy usage using the RECS 2020 data in California*



NOTES: The bar graph illustrates total energy consumption, employing logarithmic values for a more concise representation. Notably, the analysis reveals a distinct trend in energy usage distribution concerning varying income brackets. The data indicates the highest energy consumption among households with an income of $150,000. Conversely, a surprising finding shows relatively lower energy usage within the income bracket of $5,000 to $7,499. Intriguingly, households with less than $5,000 exhibit slightly higher energy utilization than those within the $5,000-$7,499 income range. This information suggests an inverse relationship between energy usage and specific income categories, indicating the necessity to explore the underlying reasons for this unexpected trend.

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Screenshot of Working Data

	moneypy	employhh	householder_race	nhsldmem	scaleb	scaleg	scalee	energyasst
1	LOWER INCOME	Employed part-time	1	1	Never	Never	Never	0
2	LOWER INCOME	Not employed	1	4	Some months	Almost every month	Never	0
3	LOWER INCOME	Retired	1	2	Never	Never	Never	1
4	UPPER INCOME	Retired	2	4	Never	Never	Never	0
5	UPPER INCOME	Employed full-time	1	1	Never	Never	Never	0
6	UPPER INCOME	Employed part-time	1	7	Some months	Never	Never	0
7	LOWER INCOME	Not employed	1	4	Never	Never	Never	0
8	UPPER INCOME	Employed full-time	4	4	Never	Never	Never	0
9	UPPER INCOME	Retired	1	2	Never	Never	Never	0
10	LOWER INCOME	Retired	1	2	Never	Some months	Never	0
11	UPPER INCOME	Employed full-time	1	3	Never	Never	Never	0
12	UPPER INCOME	Employed full-time	1	6	Never	Never	Never	0
13	LOWER INCOME	Not employed	1	1	Some months	1 or 2 months	Never	1
14	MIDDLE INCOME	Employed part-time	4	4	1 or 2 months	Some months	Never	0
15	LOWER INCOME	Retired	2	3	Never	Never	Never	0
16	LOWER INCOME	Retired	1	3	Some months	Some months	Never	0
17	MIDDLE INCOME	Retired	1	4	Some months	Never	Never	0
18	MIDDLE INCOME	Retired	4	2	Never	Never	Never	0
19	MIDDLE INCOME	Employed full-time	1	1	Never	Never	Never	0
20	LOWER INCOME	Employed full-time	4	2	Never	Never	Never	0
21	LOWER INCOME	Employed full-time	1	5	Almost every month	Never	Never	1
22	LOWER INCOME	Employed part-time	2	1	Never	Never	Never	0
23	LOWER INCOME	Retired	1	2	Almost every month	Almost every month	Never	0
24	LOWER INCOME	Retired	1	1	Almost every month	1 or 2 months	1 or 2 months	0
25	UPPER INCOME	Employed full-time	4	2	Never	Never	Never	0
26	MIDDLE INCOME	Retired	1	1	Never	Never	Never	0
27	LOWER INCOME	Not employed	2	2	Some months	Some months	Some months	0
28	UPPER INCOME	Not employed	1	4	Never	Some months	Never	0
29	UPPER INCOME	Employed full-time	6	3	Never	Never	Never	0
30	UPPER INCOME	Employed full-time	1	6	Never	Never	Never	0
31	UPPER INCOME	Retired	1	3	Never	Never	Never	0
32	LOWER INCOME	Retired	1	1	Never	Never	Never	0
33	LOWER INCOME	Not employed	1	1	1 or 2 months	1 or 2 months	Never	1
34	UPPER INCOME	Employed full-time	1	3	Never	Never	Never	0
35	MIDDLE INCOME	Retired	1	2	Never	Never	Never	0
36	LOWER INCOME	Retired	1	1	Never	Never	Never	0
37	LOWER INCOME	Retired	4	1	Never	Never	Never	0
38	MIDDLE INCOME	Not employed	1	2	Never	Never	Never	0
39	UPPER INCOME	Employed full-time	1	2	Never	Never	Never	0

Showing 1 to 39 of 1,136 entries, 18 total columns

	moneypy	employhh	householder_race	nhsldmem	scaleb	scaleg	scalee	energyasst	energyasst20	energyasst19	typehuq	sqftest	totalbtu	totaldol	e
1	12	2	1	1	0	0	0	0	-2	-2	2	1630	58496.25	487.81	
2	9	4	1	4	2	1	0	0	-2	-2	3	1750	39937.69	2250.57	
3	9	3	1	2	0	0	0	1	1	1	1	780	73291.53	2665.59	
4	15	3	2	4	0	0	0	0	-2	-2	2	1500	97641.74	3414.81	
5	15	1	1	1	0	0	0	0	-2	-2	2	2070	60489.70	2046.49	
6	15	2	1	7	2	0	0	0	-2	-2	2	2100	81478.81	4657.33	
7	12	4	1	4	0	0	0	0	-2	-2	1	1150	30706.19	1252.14	
8	16	1	4	4	0	0	0	0	-2	-2	2	1950	82136.61	2651.20	
9	16	3	1	2	0	0	0	0	-2	-2	2	5000	186944.50	6330.24	
10	12	3	1	2	0	2	0	0	-2	-2	2	2750	77429.89	2481.38	
11	15	1	1	3	0	0	0	0	-2	-2	2	1230	95433.39	3023.62	
12	16	1	1	6	0	0	0	0	-2	-2	2	2000	133684.22	4634.12	
13	4	4	1	1	2	3	0	1	1	1	4	850	24684.19	649.89	
14	14	2	4	4	3	2	0	0	-2	-2	2	1000	34367.75	1581.00	
15	9	3	2	3	0	0	0	0	-2	-2	2	1920	51457.08	927.67	
16	8	3	1	3	2	2	0	0	-2	-2	2	1900	81624.32	2644.04	
17	13	3	1	4	2	0	0	0	-2	-2	2	1400	80362.51	2625.64	
18	14	3	4	2	0	0	0	0	-2	-2	2	1780	48378.83	836.53	
19	14	1	1	1	0	0	0	0	-2	-2	5	650	16173.01	737.92	
20	12	1	4	2	0	0	0	0	-2	-2	2	1000	42916.43	980.49	
21	10	1	1	5	1	0	0	1	0	1	5	900	43614.07	729.77	
22	7	2	2	1	0	0	0	0	-2	-2	2	740	60582.17	1315.47	
23	7	3	1	2	1	1	0	0	-2	-2	1	400	39413.52	1019.21	
24	5	3	1	1	1	3	3	0	-2	-2	2	780	41274.49	501.19	
25	15	1	4	2	0	0	0	0	-2	-2	5	680	16801.68	576.68	
26	14	3	1	1	0	0	0	0	-2	-2	2	2300	28393.41	1317.01	
27	4	4	2	2	2	2	2	0	-2	-2	2	920	43082.88	1002.56	
28	16	4	1	4	0	2	0	0	-2	-2	2	1300	66938.08	1953.48	
29	15	1	6	3	0	0	0	0	-2	-2	2	2220	72714.69	2382.22	
30	16	1	1	6	0	0	0	0	-2	-2	2	1400	57387.81	1851.72	
31	15	3	1	3	0	0	0	0	-2	-2	2	1700	120937.73	3478.45	
32	10	3	1	1	0	0	0	0	-2	-2	1	1290	20816.41	491.18	
33	3	4	1	1	3	3	0	1	1	1	5	720	24273.82	413.33	
34	16	1	1	3	0	0	0	0	-2	-2	2	1290	40718.70	969.51	
35	13	3	1	2	0	0	0	0	-2	-2	2	2100	29761.63	1798.65	
36	8	3	1	1	0	0	0	0	-2	-2	5	780	23931.90	277.65	
37	12	3	4	1	0	0	0	0	-2	-2	1	1460	24950.62	593.77	
38	14	4	1	2	0	0	0	0	-2	-2	3	850	15571.84	611.69	
39	15	1	1	2	0	0	0	0	-2	-2	2	1700	49758.04	2000.06	

Showing 1 to 39 of 1,136 entries, 17 total columns

Working data is at the state level (California) in 2020, and each row corresponds to household information.

- The outcome variable is energy assistance (‘*energyasst_dummy*’) and is represented as a dummy variable.
- The primary explanatory variable, annual household income (‘*moneypy*’), is categorical, utilizing response codes from 1 to 16, each representing an income bracket that increases in scale as the code number rises.