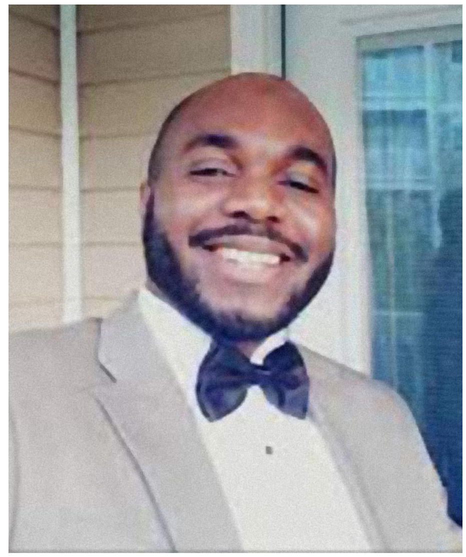
ENERGY IMPOVERISHMENT AND ENERGY INSECURITY IN THE UNITED STATES

Photo: Jon Moore

Groundswell

About the Author



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Acknowledgments

The author gratefully acknowledges the LIFT Solar for All project, colleagues, sponsors, internal reviewers, and external reviewers who supported this research.

Abstract

Date of submission: September 12, 2021

Equitable energy distribution has long been an issue of concern when studying the prevalence of high energy burdens, as not many low-income households benefit from energy-efficiency programs that are designed to reduce economic hardship and poverty. Rather, many low-income households continue to live in older homes, which are often characterized by structural issues such as poor insulation, inefficient HVAC systems, leaky roofs, inefficient and sometimes oversized appliances which increase energy costs. Despite energy abundance in the US and the propagation of energy efficiency programs and weatherization policies, low-income households continue to pay high energy bills while their environmental, social, and economic conditions have eroded. This paper sought to assess opportunities that offer the greatest hope to reduce energy burdens in the US. The result of this analysis shows regional imbalances in energy burdens, which are greatest in the Southeast and Northeast regions of the country. The results in this paper show that utility bills, housing stock and poverty rate present a threat to affordability of residential housing in the US. Most LMI households are energy impoverished, and more than two-thirds experience energy burdens that are above double digits. As a result of these findings, this study recommends that energy efficiency be viewed as economic policy to reduce poverty and improve housing, and that energy efficiency and assistance programs be focused to support low-income households.

Keywords: energy poverty, low-income, energy burden, energy assistance, utility bills, climate change.

JEL Classification: C10, C38, C55, Q40, Q41, Q47 and Q54

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Contents

1. Introduction and Background

Household energy consumption patterns have evolved since the 1970s following the inception of the Weatherization Assistance Program (WAP) and the Low-Income Home Energy Assistance Program (LIHEAP) by the US Congress. Energy is a necessity that affects every facet of life be it health, housing, education, or mobility (Brown et al., 2020). However, alarmingly, despite energy abundance in the US coupled with the propagation of energy efficiency, bill-payment assistance programs, and weatherization programs, low-income households continue to pay high energy bills while their environmental, social, and economic conditions erode. Equitable energy distribution has long been an issue of concern when studying the prevalence of high energy burdens, and there is far greater eligibility and need to participate in existing bill payment assistance and weatherization programs than there is availability. Rather, many low-income households continue to live in older homes, which are often characterized by structural issues such as poor insulation, inefficient HVAC systems, leaky roofs, and inefficient and sometimes oversized appliances that increase energy costs (Brown et al., 2020).

At-risk and disadvantaged communities throughout the nation are now advocating fairness and transparency in the design and distribution of clean energy programs. By implication, it is not just clean energy that matters — as it has previously been propagated by the literature — but the way the distribution of clean energy enhances equity and transparency and enables poverty reduction in the economy (Curti et al., 2018). Additionally, many customers now struggle to pay their utility bills due to the unprecedented economic, social, and health challenges of the COVID-19 pandemic that decimated household disposable income and altered families' ways of life. Despite recent events, underserved communities have experienced higher electricity and natural gas bills, even as their environmental, social, and economic conditions eroded. This combination of factors results from and is made worse by high unemployment, poor housing conditions, limited access to social amenities, lack of access to credit, poverty, utility default, higher than average eviction rates, historic segregation, the continuing impacts of redlining, and a lack of trust between utility customers and utility providers. Because of this, disadvantaged communities continue to be disproportionately impacted by higher, inequitable energy burdens, threatening low- and moderate-income (LMI, hereafter) households with housing instability beyond that caused by income insecurity, compared to communities occupied by residents in wealthier income groups. This inequity places great responsibility on state and local governments, which have the authority to take actions such as advancing new energy efficiency programs, increasing the transparency of energy efficiency in rental housing, and improving enforcement of building codes.

Over the past decade many studies have examined the effects of energy burden on LMI households across major cities of the United States (often termed Metropolitan Statistical Areas - MSAs), as well as suburban communities. The term energy burden[1] as used in this study describes an array of complex issues such as poverty, equity, and quality of life. McCormick (2015) highlighted the importance of clean energy efficiency programs that reduce rural energy burdens. The paper by McCormick (2015) established that LMI residents in rural communities face enormous challenges such as energy inaccessibility and energy affordability. In another study, Shoemaker et al. (2018) found that regional specificity is a key factor in determining energy burdens, which are higher for LMI residents in rural communities. Energy burden is also often considered a social

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[1] Energy burden is calculated as the mean household energy bill (electric and gas) as a percentage of the mean household income.

and environmental issue requiring justice to fully understand ways of improving energy equity for vulnerable populations (Hernandez, 2015). In a recent study by Wang et al. (2021), energy poverty varies across demographics, with African American households more vulnerable than White, Asian, and other minority group households.

Similarly, other studies have examined the implications of high energy burdens on health and wellbeing. Proponents of this theory argue that energy burden increases stress due to economic hardship and poverty. In a similar vein, low-income communities experience greater susceptibility to respiratory diseases linked to poor living conditions often characterized by structural issues such as inadequate heating and cooling systems which are known to aggravate respiratory concerns and impact mental health (Wright, 2004, Hernandez & Bird, 2010, Liddell & Morris, 2010, Dear & McMichael, 2011, Li et al., 2014, & Reames et al., 2021).

The existing literature suggests that LMI households pay significantly more for electricity bills than the average household. When studying the evolution of energy burdens in the US using Census Bureau 2011 and 2013 American Housing Survey, Drehobl and Loss (2016) found the average energy burden for all US cities was 3.5% of household income, whereas LMI energy burden stood at approximately 7.2%. Energy burdens for the African American households were 5.4% as compared to 4.1% for Latino households based on the sampled data for the MSAs. Although the drivers of household energy burden are multifaceted — including physical, economic, behavioral, and policy related causes — there is no common energy burden threshold. According to Colton (2017),[2] an energy burden threshold of 6% is often considered an unaffordable margin. An affordability threshold of 6% to 11% of annual median income (AMI) seems to be a reasonable energy burden threshold (Fisher, Sheehan & Colton, 2015., Liddel et al., 2012). These unsustainable energy burdens are the result of utility bills accounting for approximately 8% of low and moderate household incomes, leaving LMI households with tough choices to make about keeping the lights on versus paying for other necessities such as food or medicine (Drehobl and Ross, 2016).

Existing literature has not yet established strong evidence of a relationship between energy burden and energy prices[3] nor is there sufficient empirical evidence of the relationship between energy burden and individual utility account default rates. This paper seeks to provide answers to the following research questions:

- What is the energy burden landscape in the US?
- What is the relationship between energy burden and energy prices, characterized by average monthly bill payment?
- What opportunities offer the greatest hope to reduce energy burdens for LMI households?
- What is the relationship between energy burden and climate change as the United States continues its transition to a more renewable and efficient energy system?

This paper begins by discussing four theoretical strands of the energy burden-LMI nexus in section 2, while section 3 describes developmental evidence, to include energy burden trends and non-parametric statistical analysis for methodological comparisons and conceptual soundness. Section 4 discusses data and results. These sections are followed by research backed solutions to energy burden challenges in the US in section 5. The objective of this section is to determine if energy efficiency programs and upgrades are effective in reducing energy burden. Section 6 is the conclusion.

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[2] What is the Home Affordability Gap?
[3] This is based on the hypothesis that low prices do not necessarily mean low bills (Drehobl and Ross, 2016).

2. Literature Review

The term 'energy burden' has become a key conceptual construct used to measure energy related financial inequity experienced by LMI households and inform program and policy decisions that aim to include LMI households in solar energy program designs. Patterns of energy consumption have changed partly due to high energy demand and consumption as well as shifts in demographics. According to Brown et al. (2020) and Drehobl and Ross (2016), high energy burdens have causes ranging from a variety of outside factors and may be economically driven, behaviorally related, and/or physically motivated by policy-oriented determinants. This wide variation is perhaps due to diversity in the way LMI households are defined. Table 1 provides a summary classification of the high energy burden dichotomy.

Table 1: *Classification of High Energy Burden*

Classification	Definition	Type of driver
Energy burden	Energy burden is defined as the total household utility expenditures for heating and cooling as a percentage of total income	Economic (Drehobl & Ross., 2016).
Energy poverty	Measured by the degree to which access to energy (including fuels) is granted or restrained.	Economic, policy
Energy access	Energy affordability, energy reliability, energy sustainability or accessibility to clean energy	Policy and Social
Energy insecurity	Vulnerability to utility disconnection, evictions, and/or default	Economic and Behavioral

Source: Drawn from Brown et al. (2020) and Drehobl and Ross (2016),

Economic and health conditions such as loss of job or severe illness may affect an individual's ability to meet their monthly utility bill payments which can lead to involuntary default. It has been shown that most LMI households live on chronic persistent hardship which is often characterized by living paycheck-to-paycheck. Additionally, LMI households may not be able to meet monthly utility bill obligations due to high upfront energy costs which are not applied evenly to all customers based on income levels by the utilities. LMI household energy burdens can be reduced if utilities can develop a framework where fixed charges are determined based on income brackets. Reina and Kontokosta (2017) studied how regulations and energy efficiency programs help improve renters in multifamily housing. The result of this study suggests that it is equally important for LMI homeowners to understand energy conservation practices to decrease energy use. This uneven energy use is aggravated by extreme weather conditions that raise the need for cooling and heating because residences occupied by LMI households are often characterized by structural issues such as poor insulation, inefficient HVAC systems, leaky roofs, and inefficient and sometimes oversized appliances which increase energy costs.

2.1 Energy Burden

Drehobl and Ross (2016) studied the correlational effects of energy burden using data from the 2011 US Census Bureau and 2013 American Housing Survey of low-income households across 48 US cities. Low-income is defined as residents whose income is less than or equal to 80% of area median income (AMI). Several segmentations were used in Drehobl and Ross (2016) analysis for the data such as the percentage of LMI residents in single family, multifamily homes, rental, and owner-occupied homes. The study finds that low-income households and minority households in single and multifamily residences experienced higher energy burdens when compared to 3.5% of the median energy burden across all cities in the US. The study also showed regional imbalances in energy burdens which are greatest in the Southeast and Midwest regions of the country.

In another study, Kontokosta et al. (2019) examined over 13,000 multifamily residential properties in the US and found that the energy burden for LMI households in multifamily housing was 7% compared to 2% for higher income households. The motivation of the paper stemmed from the fact that rent, transportation, and utility bills are often considered to be the three main components of housing affordability. Of these three measures, energy costs are the most misconceived, and ironically, result in the greatest financial burdens on LMI households. In a similar vein, Cook and Shah (2018) used exploratory research based on interviews to assess the Colorado Energy Office strategy of using solar electricity generation to curb energy burden for LMI residents. Three energy burden classifications were derived as follows: (a) 'energy stressed' – 4%-7%, (b) 'energy burdened' householders – 7%-10% and (c) 'energy impoverished households' – 10% and over. Cook and Shah (2018) recommended proven strategies for designing and implementing low-income solar programs in the State of Colorado as well as other US states. Meanwhile, Buylova (2020) used census tract data to identify high energy burden areas across major US cities. Additionally, Hernandez and Phillips (2015) examined energy burdens caused by structural issues and poor housing conditions for a sample of 20 low-income households in New York City using surveys and interviews. The study determined that weatherization is necessary, but it is not sufficient to address structural issues facing LMI communities.

2.2 Energy Affordability

Several studies have focused on energy affordability. It is alarming that despite energy abundance in the US coupled with the propagation of energy efficiency, bill-payment, and weatherization programs, LMI households continue to pay a higher percent of their income for energy (Heindl, 2015, & Brown et al., 2020). According to Li et al. (2014) low-income residents in rural and minority communities are left behind in their pursuit of economic welfare as they continue to pay more for electricity and fuel. This paper finds that energy burdens are severe in the South compared to other regions of the US (also see Drehobl & Ross, 2016., Brown et al., 2020 & Li et al., 2014). In a different study, Ray et al. (2019) assessed the relationship between utility voucher and electric bills for over 19,000 residential households in Florida and arrived at the conclusion that utility bills present the greatest threat to affordability of residential housing. Using a logistic regression model, Mohr (2018) investigated fuel poverty in the US using data from the 2009 Residential Energy Consumption Survey. This study distinguished energy burdened renters and homeowners based on income variations. The results from this study reveal a strong correlation between fuel poverty and income distribution in the US.

2.3 Energy Poverty

Another strand of the literature focuses on the social and economic effects of energy burden on wellbeing. Energy poverty results from low-income households living in homes deprived of basic energy needs such as lack of electric heating or modern cooking fuels. Hilbert and Werner (2016) studied energy poverty for New York households that cannot properly heat-up their homes, while Chai et al. (2021) investigated the implications of rising energy prices for 63,000 residents in Queensland, Australia. These studies show that energy accessibility and affordability are key factors that can help reduce energy poverty for LMI households. In a similar vein, Bohr and McCreery (2020) assessed the relationship between energy burden and poverty in the US between 1999 and 2017. Energy burden emanates when a household spends at least 10% of its income on electricity and heating services. This study finds that income is the main determinant of energy burden, while utility rates amounted to a lesser proportion of the variation in energy rates among LMI residential households. Using a panel data analysis, the study concluded that at-risk households had 150% - 200% probability of transitioning to economic hardship and poverty over a two-year horizon relative to their non-burdened households. The conclusion drawn from this study is that energy burden has the tendency of precluding low-income households from enjoying sustainable long-term economic growth. As a result, Bohr and McCreery (2020) recommended energy efficiency and assistance programs aimed at low-income households. Most studies on energy burden and fuel poverty have been conducted in the US, but little research has been done at the international level. Most recently, Chai et al. (2021), used a microsimulation model to study the energy poverty in Queensland, Australia for approximately 63,000 residential households. This study tested correlations of households with energy poverty in relation to their ability to meet rising energy prices. Precisely, the study captured the price elasticity of energy prices to the total number of households with energy poverty within a given region. Chai et al. (2021) arrived at the conclusion that energy poverty is unevenly distributed across Australia. Therefore, income disparities, weatherization, and demographic imbalances account for most of the energy poverty in Queensland, Australia, according to the study's findings.

2.4 Energy Insecurity

Energy insecurity has emanated from the uncertainty in bills payment when a low-income resident is not able to meet their monthly obligations. Vulnerability arises from the fear of being disconnected from energy services, especially in the south as compared to other regions of the US. This is partly explained by the fact that HVAC systems in the south are predominantly electric as compared to natural gas which tend to be more affordable in other regions of the US (Elnakat et al., 2016).

3. Developmental Evidence

The dataset used in this section is derived from the National Renewable Energy Laboratory (NREL, 2021) Solar for All project. The NREL provides census tract data for both LMI and non-LMI households. One limitation with this dataset is that it is only available at the census tract level. However, given the popularity of this dataset, it is robust enough to capture the intended objectives of this paper: to assess opportunities that offer the greatest hope to reduce energy burdens in the US. The term "energy burden" as used in this study is defined as the total household utility expenditures for heating and cooling as a percentage of total income (Drehobl and Ross, 2016 & Brown et al., 2020). This definition of energy burden excludes water and transportation expenditures.

3.1 Energy Burden Trends

As evidenced from the literature review, several studies have focused on energy affordability for LMI households. This literature shows that energy providers expect consumers to pay their household energy bills or face disconnection, while consumers worry about ability to pay. Proponents of the affordability theorem argue that low-income households continue to pay more on energy bills despite energy abundance and bills-payment programs and weatherization policies in the US. (Heindl, 2015., Brown et al., 2020 & Li et al., 2014). In this paper, energy burden is used as a proxy for energy affordability. Figure 1 below shows monthly LMI electricity expenditures, while figure 2 depicts fuel and gas expenditures for LMI households.

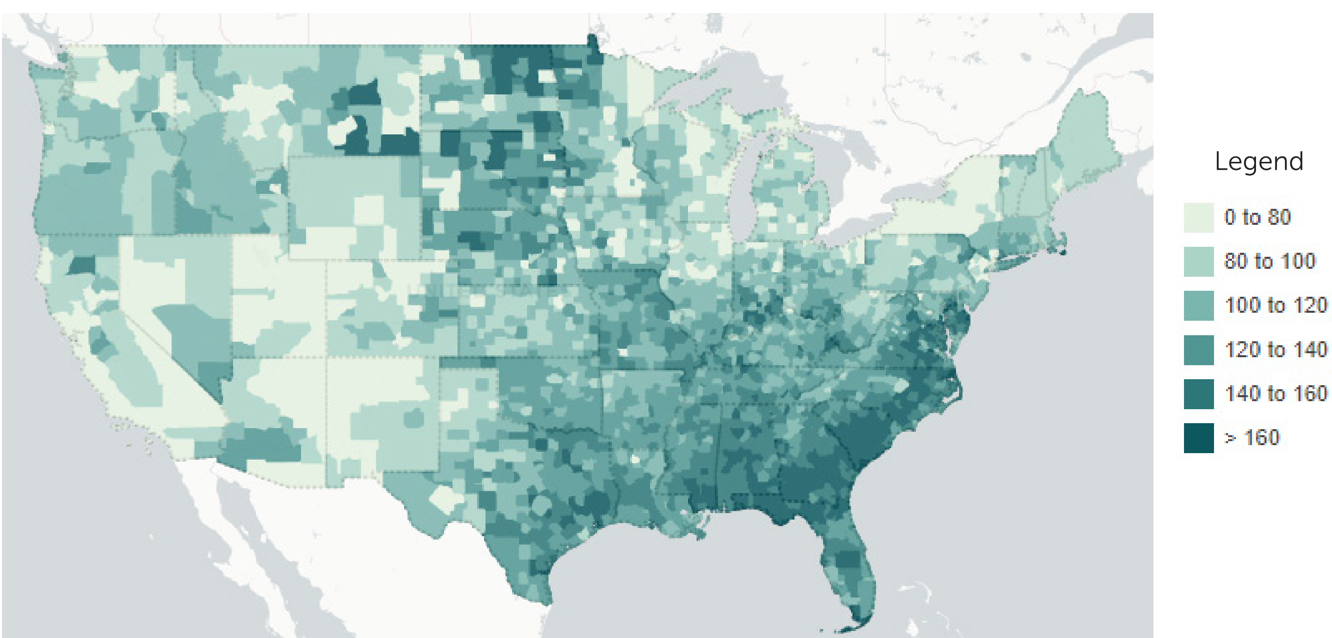

Figure 1: *LMI Households Electricity Expenditures (source, NREL)*

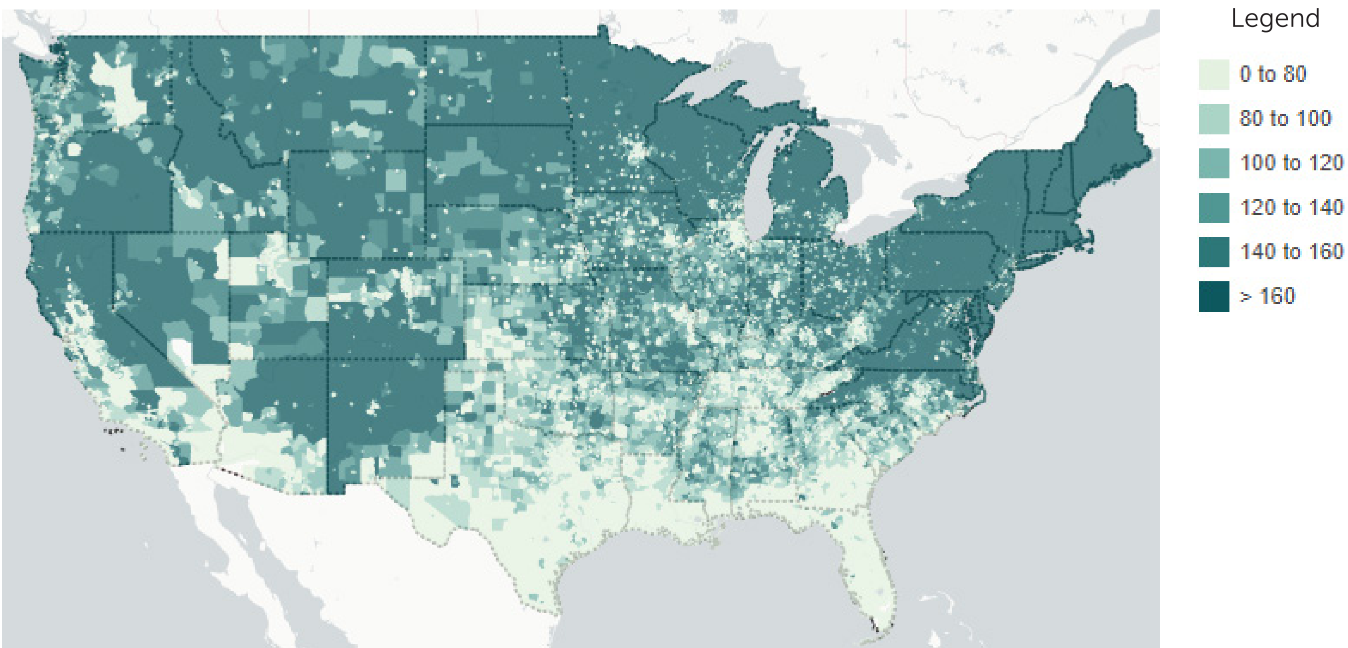

Figure 2: *Fuel and Gas Expenditures for LMI Households ($/month). Source (NREL)*

As evidenced in these graphs, energy burdens are not distributed evenly. The lightest color on both graphs shows a monthly energy expenditure of $80 or less, while the darkest shades depict monthly energy burdens exceeding $160 a month for LMI households. The result of this analysis suggests that high energy burdens have a higher concentration in the south compared to other regions. To gain a better understanding of the energy burdens landscape at the census-tract level for LMI households, this paper augmented household incomes to consider the total amount spent on housing energy bills as shown in figure 3.

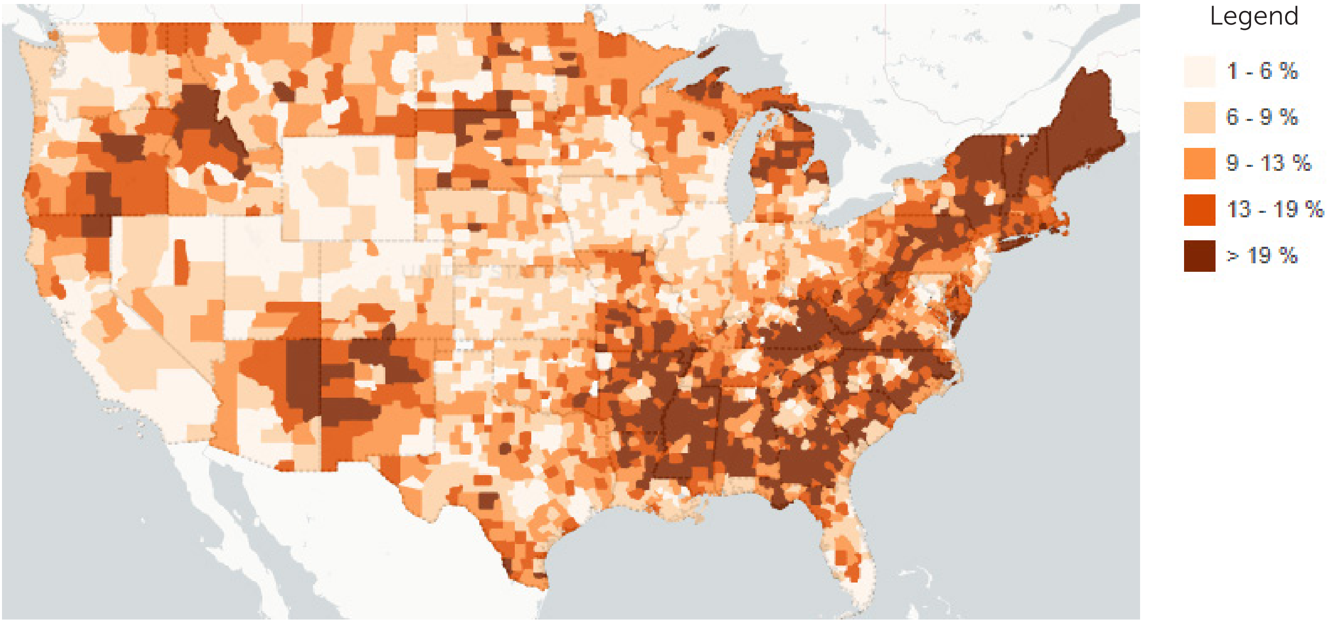

Figure 3: *Energy Burden (% income spent on housing energy bills). Source (NREL)*

This graph shows that areas with high energy burdens are sparsely distributed. The lightest color in the figure represents 6% or less of annual income spent on housing energy bills, while the northeast and southeastern regions remain heavily energy burdened, as illustrated on the graph by the darkest color, representing energy burdens of 19% or greater. To cite but a few states, these areas of high energy burdens include Maine, Vermont, New Hampshire, New York, Pennsylvania, Tennessee, West Virginia, Virginia, Kentucky, Georgia, Mississippi, South Carolina, North Carolina, and Alabama, as well as most of North Florida. As earlier mentioned in this report, the NREL data is only available at the census tract level, thereby making state comparisons difficult. To circumvent this limitation, the census-tract energy burdens are aggregated to estimate state-level energy burdens. Data aggregation as used in this paper has the following advantages: (1) to make it easier to identify trends in energy burdens for the sampled data, (2) to facilitate machine learning to derive rich dataset used in the predictive modeling section of this paper, and (3) to derive useful statistical properties of the energy burden data such as normality of the distribution. The graphical analysis of this approach is presented in the figure below for LMI and non-LMI households, while Table 2 is a ranking of energy impoverished states, applying the model developed by Cook and Shah (2018).

Figure 4: *Energy Burden Trends in the U.S.*

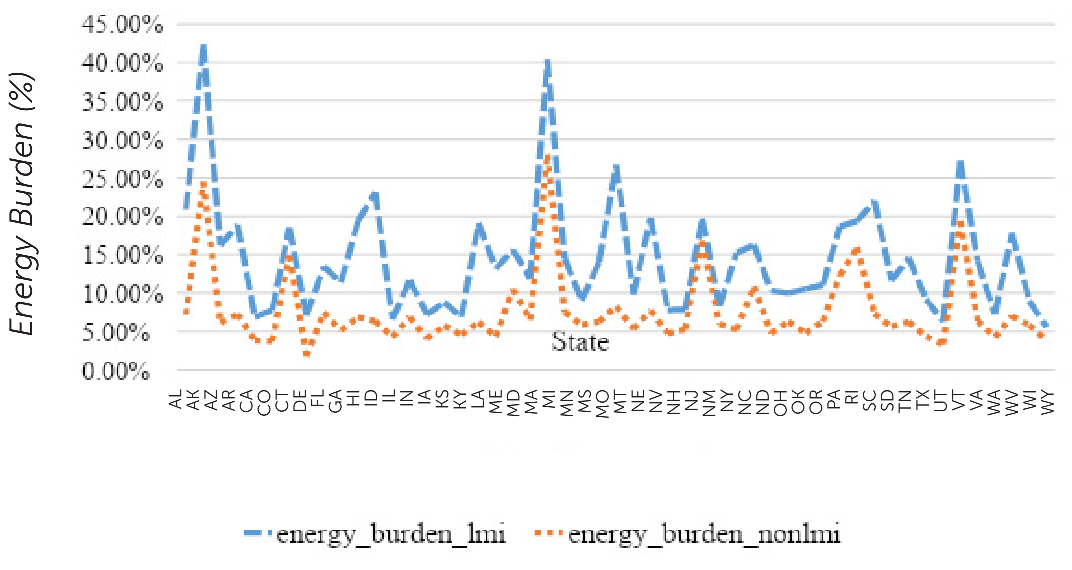

Table 2: *Energy Impoverished States*

State Abbreviation	LMI Energy Burden	Non-LMI Energy Burden
AK	42.4%	24.5%
ME	40.4%	28.0%
VT	27.2%	19.3%
MS	26.7%	8.3%
HI	23.1%	6.4%
SC	22.0%	7.3%
AL	20.9%	7.2%
NC	19.8%	7.7%
NH	19.7%	16.8%
GA	19.4%	6.9%
RI	19.4%	16.0%
KY	19.1%	6.2%
AR	18.9%	7.3%
PA	18.7%	12.3%
CT	18.5%	14.9%
WV	17.8%	7.0%
NY	16.3%	10.9%
AZ	16.2%	6.2%
MA	15.6%	10.5%
NM	15.2%	5.3%
TN	14.6%	6.3%
MI	14.5%	7.5%
VA	14.2%	6.4%
MO	14.1%	6.3%
DE	13.5%	7.5%
LA	13.2%	4.4%

MD	11.9%	6.5%
ID	11.7%	6.9%
SD	11.6%	5.6%
FL	11.4%	5.2%
OR	11.1%	6.3%
OK	10.5%	4.8%
ND	10.3%	4.8%

Note: Derived through aggregation of state county energy burdens for each state

As evidenced from the table above, 33 states (out of 50 states) have double-digit energy burden percentages, representing approximately two-thirds of LMI households, which indicates the very uneven distribution of energy burden patterns across LMI households. While heating expenses contribute to energy burdens in the Northeast, cooling expenses result in high energy burdens in the Southeast. Using the same energy classification matrix by Cook and Shah (2018), Table 3 shows that there are approximately 13 LMI energy burdened states (7% - 10%) as compared to 5 energy-stressed states (4% - 7%).

Table 3: *Energy Stressed and Energy Burdened States*

State Abbreviation	LMI Energy Burden	Non-LMI Energy Burden
OH	10.0%	6.3%
MT	9.8%	5.3%
TX	9.2%	4.4%
MN	9.0%	5.9%
WI	9.0%	5.8%
IN	8.8%	5.8%
NJ	8.3%	6.0%
NV	7.9%	5.3%
NE	7.8%	4.7%
CO	7.8%	3.8%
WA	7.3%	4.3%
IL	7.2%	4.1%
DC	7.1%	1.8%
KS	6.9%	4.6%
CA	6.9%	3.8%
IA	6.6%	4.3%
UT	6.3%	3.3%
WY	5.6%	3.9%

Note: Derived through aggregation of state county energy burdens for each state

3.2 Energy Burden Comparisons – A Non-Parametric Statistical Analysis

Having examined LMI household energy burden trends in the previous section, this section provides further comparisons of energy burdens at the aggregated census-tract and MSA levels respectively for methodological soundness. Drehobl and Ross (2016, p. 47) reported highest quartile energy burdens for major cities for LMI households. The statistical definition of highest quartile as used in the paper by Drehobl and Ross (2016) is considered the maximum percentile (representing the 4th quartile of the distribution) for each major city. Table 4 represents a comparative analysis of energy burdens at the MSA level and aggregated census-tract level.

Table 4: *Energy Burden Methodological Comparisons*

City	State	Drehobl and Ross (2016)	Moleka (2021)
Atlanta	GA	18.24	19.4
Baltimore	MD	13.65	11.91
Birmingham	AL	18.82	20.87
Boston	MA	12.36	15.63
Charlotte	NC	14.45	19.8
Detroit	MI	15.26	14.49
Indianapolis	ID	12.83	11.72
Kansas City	MO	14.6	14.06
Louisville	LY	12.74	19.11
Memphis	TN	25.47	14.6
Miami	FL	11.04	11.4
Minneapolis	MN	8.2	9.04
New York City	NY	14.01	16.26
Philadelphia	PA	16.67	18.67
Phoenix	AZ	13.42	16.19
Richmond	VA	11.51	14.16
Seatle	WA	8.05	7.31
St Louis	MO	17.78	14.06
Virginia Beach	VA	12.61	14.16
	Average	**14.300%**	**14.88%**

It may seem at first glance that energy burden percentages at the MSA levels are lower than those at the state-level. This may be explained by the fact that the state-wide energy burden includes rural areas, with historically higher energy burdens because housing stocks are rental with high structural issues, as studies show (Li et al., 2014, McCormick, 2015 & Shoemaker et al., 2018). This suggests that rural areas tend to be disaggregated by energy burdens. However, the combined average of the MSAs and the state-wide are quantitatively unchanged as evidenced in Table 4 above. This brings us to the next section, which examines if both datasets come from the same distribution.

3.2.1 Non-Parametric Statistical Analysis

Without assuming normality about the distribution, we test at the 5% level to determine whether energy burdens between the MSA and State levels are identical to each other or if the energy burdens differ from both populations. Under the null hypothesis, H_0, the samples come from the same population, as against the alternative hypothesis, H_1 that they are different – meaning the MSA energy burdens cannot be used as a proxy for the state-wide energy burdens and vice-versa. We applied a battery of non-parametric tests to explain if there are any differences between both datasets.

The Mann-Whitney (1947) U test, also called the Wilcoxon rank-sum test, compares two unpaired distributions, based on the assumption that each datapoint is sampled independently from the same distribution. The Mann-Whitney test is used when the sample sizes are small ($n<30$), and the distributions are not normally distributed.[4] The U-test examines if two groups have the same median, which seem appropriate for use in comparing MSA and State-wide energy burdens. Under the null hypothesis, there is no difference between the median values of the two data distributions as against the alternative hypothesis that there exists a significant variation. The test statistics, U is defined as:

$$U = n_1 + n_2 + \frac{1}{2n_1}(n_1 + 1) - T \qquad (1)$$

where, n_1 and n_2 are the number of observations in both groups, and T is the sum of ranks from the group containing the least observations.

The Kruskal-Wallis (1952) non-parametric test allows comparison of the median of more than two populations. Assuming k independent samples each of size n_j, $j = 1, \ldots, K$, the Kruskal-Wallis one way analysis of variance (ANOVA) tests the hypothesis that the samples come from the same continuous population. Given that $R_j = \sum_{i=1}^{n_j} rank(X_{ij})$ is the sum of all ranks in the j[th] sample and $n = \sum_{j=1}^{k} n_j$ is the total number of observations in the K samples, the test statistics is defined as:

$$H = \frac{12}{n(n+1)} \sum_{j=1}^{k} \frac{R_j^2}{n_j} - 3(n+1) \qquad (2)$$

Table 5 below, provides a summary of the non-parametric tests results.

Table 5: Analysis of Non-parametric Test Results

Test Type	Test Statistic	P-value
Mann-Whitney – 2 tail test (2TT)	W = 148.5	0.3577**
Mann-Whitney – 1 tail test (less)	W = 148.5	0.1788**
Mann-Whitney – 1 tail test (greater)	W = 148.5	0.8287**
Wilcoxon – signed rank exact test	V = 59	0.1564**
Kruskal-Wallis rank sum test	Chi-squared = 17.795	0.3361**

Note: W is the Wilcoxon rank sum test. ** indicate significance at the 5% level.

Observing that the p-values are greater than 0.05 in all cases, we do not reject the null hypothesis, meaning that the aggregated energy burden averages are similar for the sampled data. The next section provides an empirical analysis of the energy burden-LMI nexus.

[4] The Mann-Whitney U test is the non-parametric equivalent of the two-sample independent test.

4. Data and Results

This section briefly introduces a multivariate logistic regression model as a method of analyzing the determinants of high energy burdens in LMI households in the United States. The use of a predictive analysis model is to capture the effects of energy burden (measured as a binary outcome variable) on the resultant explanatory variables as probabilities. First, we focus on the general framework of reasonability analysis by defining the dataset, which is based on aggregated census-tract data, augmented with publicly available macroeconomic data, as indicators for each state. Second, the economic theoretical expectation of each driver is defined for use in the logistic regression model. This is followed by the methodology and explanation of results.

4.1 Variable Definition and Transformation

The dependent variable is a binary outcome variable that takes the value of 1 for each state where the energy burdens are at least 10%, and 0 otherwise. The novelty of this approach and contributions to the literature are that not many studies have used predictive modeling to analyze the determinants of energy burdens for LMI households, augmented with macroeconomic variables, to capture the wider implications of unsustainable energy burdens that are the results of utility bills. Table 6 summarizes the dataset used in the empirical section of this paper, together with the predictors.

Table 6: *Data Sources and Definition of Variables*

Variable Type	Definition	Type of Transformation used	Driver Impact on energy burden	Data Source
Dependent variable	Energy burden	Takes the value of 1, where energy burden >= 10 and 0 otherwise	None	Aggregated from the census tract LMI household energy burden data provided by NREL.
Predictor Variables				
Unemployment rate	Seasonally adjusted	None	Positive. An increase in state-wide unemployment has a direct impact on energy burden.	US Bureau of Labor Statistics (June 2021 estimates).
Poverty rate	Percentage of persons in poverty	None	Positive – Poverty rate also directly affects energy burdens	US Census Bureau[5]
Log_hhIncome	Median Household income	Natural log	Negative – a decrease in household income reduces marginal propensity to consume such as utility bills payment.	U.S. Census Bureau
Log_avg_mbill	Average monthly utility bill	Natural log	Positive impact	Aggregated from the NREL

[5] Accessed August 2021 at: https://www.census.gov/quickfacts/fact

Housing Indicators				
Rent burden	Defined as median gross rent as a percentage of median monthly income	None	Positive impact. Most LMI occupants live in residential and multifamily buildings. Rent increases have a direct impact on energy burdens.	U.S. Census Bureau
Persons_pHH	Number of persons per household	None	Positive (indirect impact)	U.S. Census Bureau
Housing stocks	Total number of housing units for each state	Natural log	Negative impact	U.S. Census Bureau
Building permits	Total number of building permits for each state	Natural log	Negative	U.S. Census Bureau
Controls – Population and Demographics				
Population	State population	Natural log	Control	U.S. Census Bureau
% AfrAM	Percentage of African Americans	None	Control	U.S. Census Bureau
%Asian	Percentage of Asians	None	Control	U.S. Census Bureau
%Hisp	Percentage of Hispanic	None	Control	U.S. Census Bureau

Seasonally adjusted unemployment rate data for each state were obtained from the US Bureau of Labor Statistics[6] (June 2021 estimates). An increase in the state-wide unemployment rate has a direct impact on the energy burden levels. Studying the drivers of energy insecurity in the Southeast, William and Kelley (2021) established that the median annual income spent on energy for LMI households is between 10% and 13%. There may be several physical factors affecting this. For example, the aging housing stock is one main driving factor. The study by William (2021), shows that 57% of all residential homes in the Southeast were created before recent energy efficiency legislation. According to this study, the old energy-inefficient homes paired with hot summers and temperate winters, where heating and cooling are often used, drive energy bills up. Pennsylvania[7], Maine, and Michigan are also found to have old housing stocks. According to the National Center for Health Housing (2015) approximately 40% of housing units in Pennsylvania were built before 1940 and specifically in Philadelphia, 95% of housing units were built before 1978. Studying the prevalence of energy burdens in Maine, Rector (2019) found that about 25% were built before 1940 and Michigan's[8] is at around 17%.

Maine has the added physical issue that a little over 40% of LMI households use propane as their primary heating fuel. Propane is the most expensive heating fuel, more than twice the price of natural gas, electricity, and fuel oil (Allison et al., 2019). The high number of old non-energy efficient housing units, especially in states like Maine where the fuel type is extremely expensive, are causing LMI households to pay a large percentage of their annual income for energy. Figure 5 shows the correlation plot, with histograms, density functions, smoothed lines, and correlation coefficients for the predictor variables. These visuals are assembled to enable visualization of no evidence of multicollinearity between the explanatory variables.

[6] Accessed August 2021 at: https://www.bls.gov/web/laus/laumstrk.htm
[7] National Center for Healthy Housing (2015). Pennsylvania Health Housing Fact Sheet. https://nchh.org/resource-library/Healthy_Housing_Fact_Sheet--Pennsylvania_2015_7.15.15_final.pdf
[8] Michigan State Housing Development Authority (2000). Michigan Housing Market Analysis. https://www.michigan.gov/documents/mshda_Section_IV_Cover_138408_7.pdf

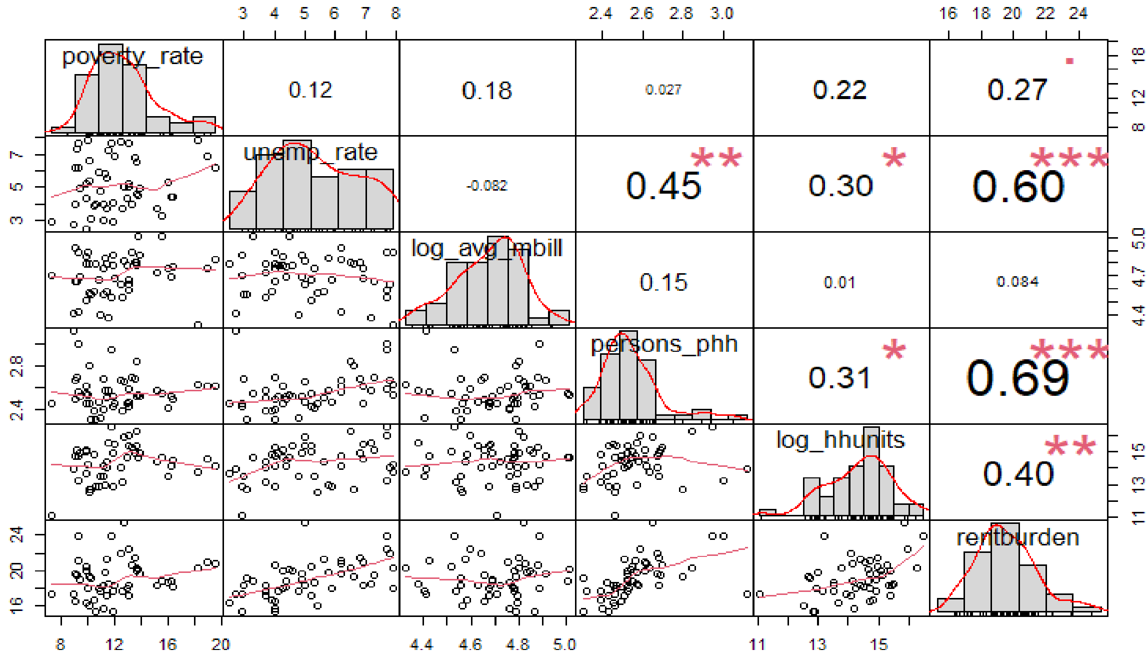

Figure 5: *Spearman's Rank Correlation between Regressors*.

4.2 Methodology

This section describes the use of a logistic regression model, which is an extension of the linear regression model for classification problems. Given that the dependent variable is a binary outcome variable, the solution for classification is logistic regression, to derive predicted probabilities of the response variable based on energy burden's predicted outcomes. In its simplest form, the logistic function is defined as:

$$logistic(\lambda) = \frac{1}{1 + exp\,(-\lambda)} \qquad (3)$$

Considering a linear model, the relationship between predicted outcomes can be defined as:

$$\hat{y}^{(i)} = \alpha_0 + \alpha_1 x_1^{(i)} + \alpha_2 x_2^{(i)} + \cdots + \alpha_p x_p^{(i)} \qquad (4)$$

Using equation (3), the right-hand side of equation (4) is converted into a probability model, with probabilities between 0 and 1 as follows as:

$$P\left(y^{(i)} = 1\right) = \frac{1}{1 + exp\left(-(\alpha_0 + \alpha_1 x_1^{(i)} + \alpha_2 x_2^{(i)} + \cdots + \alpha_p x_p^{(i)})\right)} \qquad (5)$$

Inverting the logit model forces the predicted probabilities to be bound between 0 and 1. By implication, the coefficients do not influence the logistic model linearly, unlike the linear regression model which assumes linearity. This is because the weight sum is transformed by the logistic function to a probability. The odds ratio is defined as the probability of an event occurring divided by the probability of no event. Applying the exponential function on both sides of equation (6) gives equation (7) as follows:

$$log\left(\frac{P(y = 1}{1 - P(y = 1)}\right) = log\left(\frac{P(y = 1}{P(y = 0)}\right) = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_p x_p \qquad (6)$$

$$\frac{P(y = 1}{1 - P(y = 1)} = odds = exp(\alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_p x_p\,) \qquad (7)$$

By implication, incremental increases in one unit of an explanatory variable on the predictor variable can be compared by examining the ratio of both predictors as follows.

$$\frac{odds_{x_j+1}}{odds} = \frac{exp(\alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_j (x_j + 1) + \cdots + \alpha_p x_p)}{exp(\alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_j x_j + \cdots + \alpha_p x_p)} \tag{8}$$

Applying the rule: $\frac{exp(a)}{exp(b)} = exp(a-b)$, equation (8) can be reduced to a single exponent, $exp\left(\beta_j\right)$ as follows.

$$\frac{odds_{x_j+1}}{odds} = exp\big(\beta_j(x_j + 1) - \beta_j x_j\big) = exp\big(\beta_j\big) \tag{9}$$

The results of this approach are presented in Table 7 through 10 for three competing models.[9] The binary dependent variable, is represented in equation 10 as:

$$y_i = \begin{cases} 1 & if\ LMI\ energy\ burden >= 10\% \\ 0 & Otherwise \end{cases} \tag{10}$$

Table 7: *Model Coefficients of Energy Burden Determinants.*

	Dependent variable: LMI Energy Burden >= 10.0, 1, 0		
	(Baseline)	(Demographics Weights = %AfrAm, %Asian & %Hisp)	(Controlling for Population, Weight = log (pop))
Poverty Rate	0.395*	0.458***	0.399***
	(0.221)	(0.042)	(0.057)
Unemployment Rate	0.282	0.362***	0.312***
	(0.333)	(0.075)	(0.088)
Log (Avg_monthly_bill)	6.899**	9.837***	7.161***
	(3.176)	(0.766)	(0.836)
Persons per household	-2.615	-5.453***	-3.140***
	(3.342)	(0.766)	(0.886)
Log (Housing units)	-0.664*	-0.750***	-0.666***
	(0.395)	(0.080)	(0.103)
Constant	-21.477	-27.786***	-21.531***
	(14.074)	(3.140)	(3.638)

[9] These models were estimated with an 80% to 20% train and test data respectively.

Observations	40	40	40
Log Likelihood	-18.841	-468.473	-284.218
Akaike Inf. Crit.	49.683	948.947	580.435
Note:			*p<0.1; **p<0.05; ***p<0.01

In the “Baseline Model”, the binary LMI household energy burdens are regressed against poverty rate, unemployment rate, number of persons per household as well as the natural logarithm of average monthly bill and housing stocks on a constant term. Being disproportionately affected by high energy burdens are people of color. According to the ACEEE report (2020a)[10] across the country 36% of Black households, 28% of Hispanic households, and 35% of Native American households have a high energy burden. This is especially prevalent in the South where lasting effects of segregation and lack of representation prevail. This is also prevalent for inner-cities residents in such cities as Detroit[11], Michigan, and Philadelphia[12], Pennsylvania, where around 41% of Black and Hispanic households face high energy burdens.

The “Demographic Model”, as used in this paper, extends the baseline model while controlling for the proportions of the African American, Asian, and Hispanic populations, as studies show that these groups are susceptible to high energy burdens, compared to other demographic populations. The “Population Model” controls for the variance in the entire population as an instrument. Additionally, diagnostic tests were performed to validate the coefficient estimates of the results as shown in the Table 8 below. Except for the baseline model, the variance inflation factors (VIF) are less than 2, indicating no evidence of multicollinearity. This means that the explanatory variables are not correlated with one another. Higher order autocorrelations were conducted using the Breusch-Godfrey test, while tests for heteroskedasticity were performed using the Breusch-Pagan and Goldfeld-Quandt tests. The validity of the functional specification is shown by the Rainbow and Harvey-Collier tests. In all cases, the null hypothesis of no misspecification in the functional form cannot be rejected. The results of these analyses are shown below.

Table 8: *Summary of Diagnostic Tests*

Test name	Test type	Baseline Model	Demographics	Population Controlled
Multicollinearity	Variance inflation factor	VIF > 7	VIF < 1	VIF < 1
Autocorrelation, order = 2	Breusch-Godfrey test	0.3972**	0.3972**	0.3972**
Autocorrelation, order = 3	Breusch-Godfrey test	0.3255**	0.3255**	0.3255**
Heteroskedasticity	Breusch-Pagan	0.2134**	0.2134**	0.2134**
Heteroskedasticity	Goldfeld Quandt	0.6545**	0.6545**	0.6545**
Functional form	Rainbow test	0.2525**	0.2525**	0.2525**
Functional form	Harvey-Collier test	0.1991**	0.1991**	0.1991**
Concordance		-	-	0.68

Note: Do not reject since PV > 0.05 *p<0.1; **p<0.05; ***p<0.01

[10] https://www.aceee.org/sites/default/files/pdfs/ACEEE-01%20Energy%20Burden%20-%20National.pdf
[11] ACEEE (2020b). Energy Burdens in Detroit. https://www.aceee.org/sites/default/files/pdfs/aceee-01_energy_burden_-_detroit.pdf
[12] ACEEE (2020c). Energy Burden in Philadelphia. ACEEE, 2020. https://www.aceee.org/sites/default/files/pdfs/aceee-01_energy_burden_-_philadelphia.pdf

Poverty rate, unemployment rate, the natural logarithm of average monthly electricity bill, and the natural logarithm of housing units are significant at the 5% level. These variables also have the expected signs as predicted in the literature. If the state-wide poverty rate increases by one unit, the expected change in the log-odds of an LMI household being energy burdened is 0.458 (using Model 2 as an example). Table 8 helps in depicting if the effects are positive or negative but does not, however, illustrate the magnitude of energy burdens propagated by the predicted variables. To do this, Table 9 summarizes the relative risk, otherwise termed odds ratio of each effect.

Table 9: *Relative Risk Analysis – Odds Ratio*

	Dependent variable: LMI Energy Burden >= 10.0, 1, 0		
	(Baseline)	(Demographics Weights = %AfrAm, %Asian & %Hisp)	(Controlling for Population, Weight = log (pop))
Poverty Rate	1.484*	1.580***	1.490***
	(0.221)	(0.042)	(0.057)
Unemployment Rate	1.326	1.436***	1.365***
	(0.333)	(0.075)	(0.088)
Log (Avg_monthly_bill)	991.422**	18,704.600***	1,288.474***
	(3.176)	(0.766)	(0.836)
Persons per household	0.073	0.004***	0.043***
	(3.342)	(0.766)	(0.886)
Log (Housing units)	0.515*	0.472***	0.514***
	(0.395)	(0.080)	(0.103)
Constant	0.000	0.000***	0.000***
	(14.074)	(3.140)	(3.638)
Observations	40	40	40
Log Likelihood	-18.841	-468.473	-284.218
Akaike Inf. Crit.	49.683	948.947	580.435
Note:			*p<0.1; **p<0.05; ***p<0.01

In all three models, the average monthly bill exerts the greatest impact on energy burden. Holding all things constant, when poverty rate increases by one unit, it is 1.580 times more likely to be y=1 as opposed to y=0 – meaning the odds of an LMI household being energy impoverished because of poverty is 1.580. The existing literature suggests that LMI households pay significantly more on electricity bills than the average household. These unsustainable energy burdens are the results of utility bills accounting for approximately 8% of low and moderate household incomes, leaving LMI households with tough choices to make about keeping the lights on versus paying for other necessities such as food or medicine (Drehobl and Ross, 2016).

Additionally, Table 10 shows the logit model predicted probabilities, which are derived by inverting the logit model.[13] As evidenced from this table, the probability of an LMI household becoming energy impoverished increases with average monthly bills, poverty rate, low housing stock, and unemployment rate. This research finds less evidence to support the fact that energy burdens are the direct consequence of the number of persons[14] per LMI household.

Table 10: *Predicted Probabilities of LMI Energy Burdens*

	Dependent variable: LMI Energy Burden >= 10.0, 1, 0		
	(Baseline)	(Demographics Weights = %AfrAm, %Asian & %Hisp)	(Controlling for Population, Weight = log (pop))
Poverty Rate	0.597*	0.612***	0.598***
	(0.221)	(0.042)	(0.057)
Unemployment Rate	0.570	0.589***	0.577***
	(0.333)	(0.075)	(0.088)
Log (Avg_monthly_bill)	0.999**	1.000***	0.999***
	(3.176)	(0.766)	(0.836)
Persons per household	0.068	0.004***	0.041***
	(3.342)	(0.766)	(0.886)
Log (Housing units)	0.340*	0.321***	0.339***
	(0.395)	(0.080)	(0.103)
Constant	0.000	0.000***	0.000***

[13] See Gelman and Hill (2007).
[14] This variable has a negative coefficient in Table 7.

	(14.074)	(3.140)	(3.638)
Observations	40	40	40
Log Likelihood	-18.841	-468.473	-284.218
Akaike Inf. Crit.	49.683	948.947	580.435
Note:			*p**p***p<0.01

A solution to addressing these problems is updating homes with new insulation, roofing, siding, windows, appliances, etc. to make them more energy efficient. The upfront costs to do this, however, are too much for LMI households (Drehobl et al., 2020). Drehobl et al. (2020) found that it is especially difficult for multifamily homes and renters to implement housing upgrades. Multifamily homes are much bigger and have complex heating and cooling and landlords of rented homes end up benefiting much more than the renters themselves. This is true for most states, however, Holder (2020) found that in Virginia, homeowners had higher energy insecurity than both multifamily units and renters.

5. Solutions to the Energy Burden Challenges in the U.S.

Based on the findings from this study that across the US, the average LMI household spends 14.5% or more of income on energy expenditures as compared to 7.7% for non-LMI households. This paper finds that LMI households' energy burdens double that of non-LMI households. This section is an attempt to describe opportunities that offer the greatest hope to reduce energy burdens for LMI households.

5.1 Energy Efficiency Programs

Figure 6 below shows energy efficiency gains that could be implemented to solve the energy burden problem in the US. This is because homes occupied by LMI families and individuals are often characterized by structural issues such as poor insulation. As a result, energy-efficiency programs have the potential of reducing consumption which will likely result in a reduction in household subscriber electricity costs.

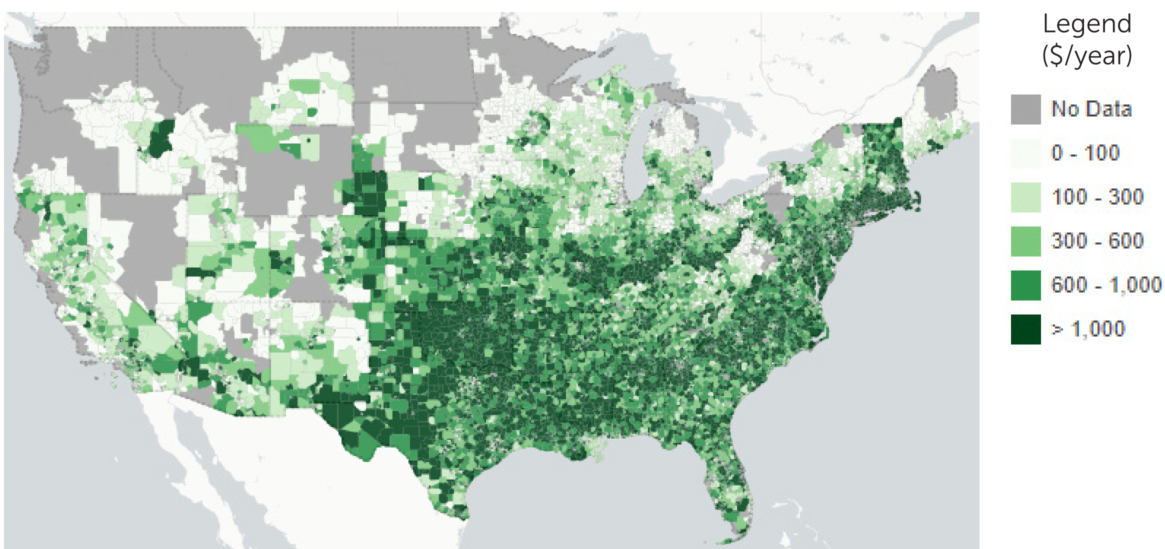

Figure 6*: LMI (AMI) Energy Efficiency Bill Savings ($/year), NREL*

As evidenced from figure 6 above, energy efficiency programs such as the installation of smart equipment could have the greatest impact in high energy burdened states. For example, the introduction of energy efficiency programs in each state could lead to $600 or more cost savings per household per year, seen by the darker shades. Electric bill savings delivered by Solar for All programs is another solution to the energy burden problem, in that this method could provide LMI families with the benefits of locally generated clean energy through efforts such as the DC Solar for All project (Daniel, 2019). Figure 7 shows electric bill savings potential for LMI households through the installation of solar panels.

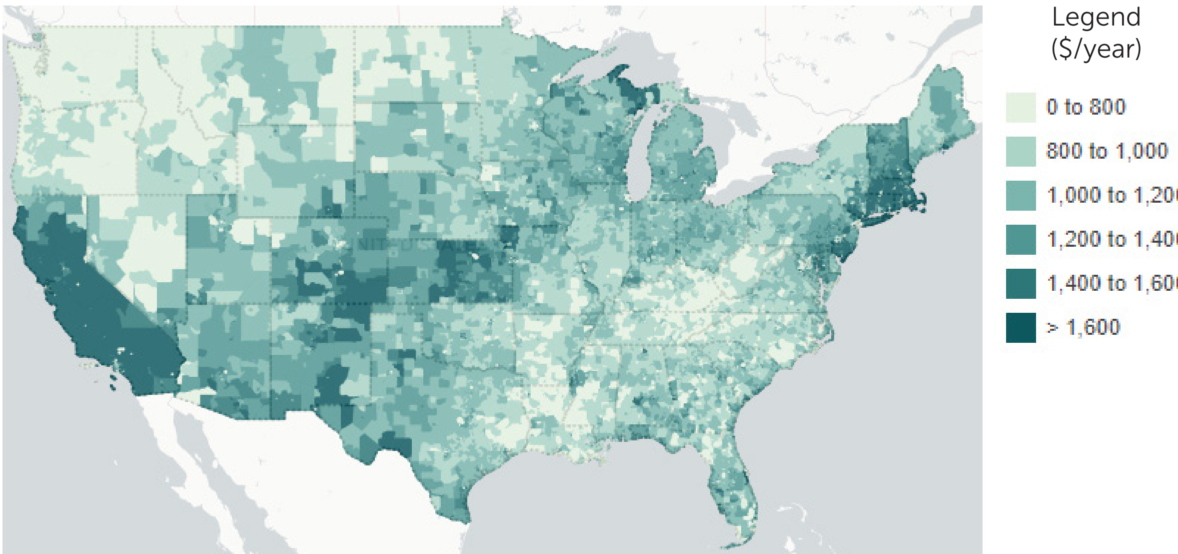

Figure 7: *Potential LMI Household Electric Bill Savings ($/year). Source – NREL.*

A less energy burdened state like California has massive electricity bill savings potential — with estimates of $1,600 or more — partly due to longer sunny hours.

5.2 Climate Change Impact

Climate change has a notable impact on energy burden, which will be discussed in this section. Flaherty et al. (2020) examined utility disconnection policies across the US caused by extreme temperatures. This proven connection between extreme temperatures and utility disconnections holds additional significance when the major temperature fluctuations predicted to come about due to climate change are considered.

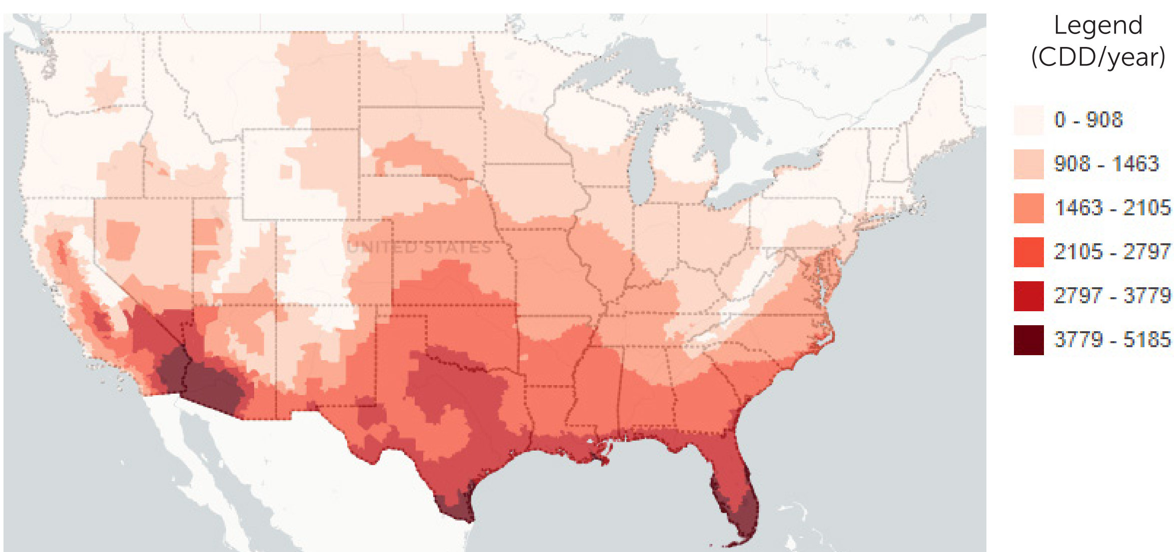

Figure 8*: Cooling Degree Days (CDD), Source – NREL*

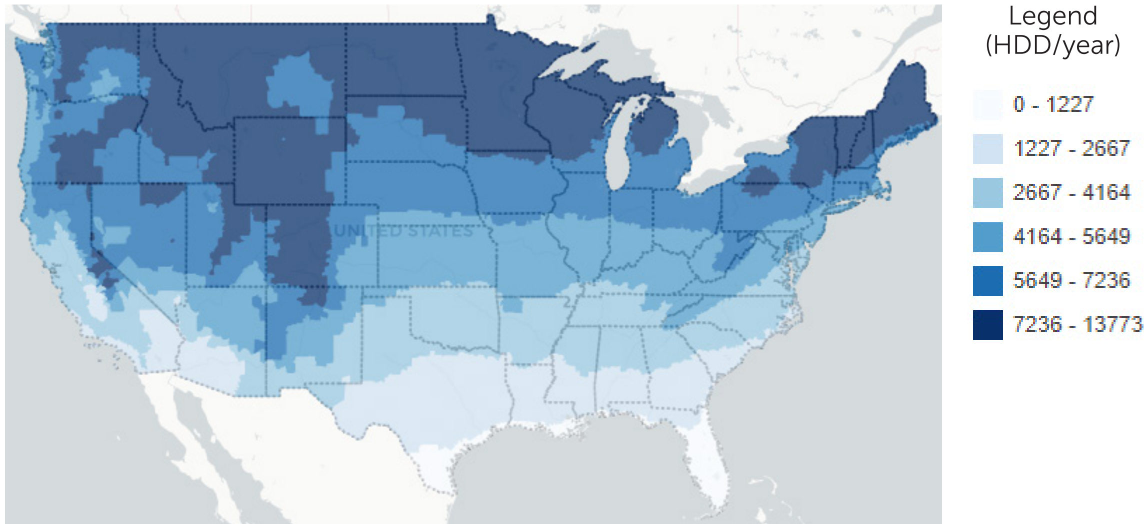

Figure 9: *Heating Degree Days, Source NREL.*

As evidenced from the graphs above, high energy burdens in the south are partly the result of extreme temperatures, which lead to longer cooling days compared to other regions of the country. This study recommends policy measures to tackle the impacts of climate change, particularly in the South, which is more susceptible to extreme temperatures due to climate change.

6. Conclusion and Policy Recommendations

Using census tract data from the NREL, augmented with publicly available macroeconomic and housing stock data from the US Census Bureau, this paper finds that energy burdens are not distributed evenly in the US. These unsustainable energy burdens are the results of utility bills, poverty rates, unemployment rates and low housing stocks presenting the greatest threat to affordability of residential housing. This study finds that LMI households have between 32% to 100%[15] probability of transitioning to economic hardship and poverty relative to their non-burdened households. Studying Colorado's energy burden in 2015, Cook and Shah (2018) estimated that low-income householders are 'energy impoverished' when total energy expenditure as a percentage of income exceeds 11%. Using the ranking developed by Cook and Shah (2018), this report finds aggregated energy burdens for LMI households to be 14.5% as compared to 7.7% based on the sample data. Using data from 2013-2014, Eisenberg (2014) also found energy burdens of 16.3% and 3.5% for low and non-low-income householders, respectively, in the US. Despite energy abundance in the US coupled with the propagation of energy efficiency, bill-payment, and weatherization programs, low-income households continue to pay more on energy bills whereas their environmental, social, and economic conditions have eroded. Equitable energy distribution has long been an issue of concern when studying the prevalence of high energy burdens, as few low-income households benefit from energy-efficiency programs designed to reduce economic hardship and poverty compared to the size of the need. Many low-income households continue to live in older homes, which are often characterized by structural issues such as poor insulation, inefficient HVAC systems, leaky roofs, inefficient and sometimes large appliances which increases energy costs. High energy burdens contribute to the widening wealth disparity between low- and high-income groups. Federal programs like LIHEAP or WAP are underfunded and only reach a portion of qualified households. According to Luis (2016), compared to all other regions, the Southeast region - states like North Carolina, South Carolina, Georgia, Virginia, Alabama - has the lowest investment in energy efficient programs. Luis (2016) showed that LMI households in Maine, Pennsylvania, and Michigan are desperately in need of more programs that help them and their energy burdens.

This paper sought to assess opportunities that offer the greatest promise to reduce energy burdens in the US. Existing literature has not yet established strong evidence of a relationship between energy burden and energy prices nor is there sufficient empirical evidence of the relationship between energy burden and macroeconomic drivers, which motivated the approach used in this paper. This study shows that LMI households pay significantly more on electricity bills than non-LMI households. The result of this analysis shows regional imbalances in energy burdens which are greatest in the Southeast and Northeast regions of the country. This is partly explained by the fact that heating systems — particularly in the South — are predominantly electric, as shown in the figure below.

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[15] These conclusions are drawn from Table 10.

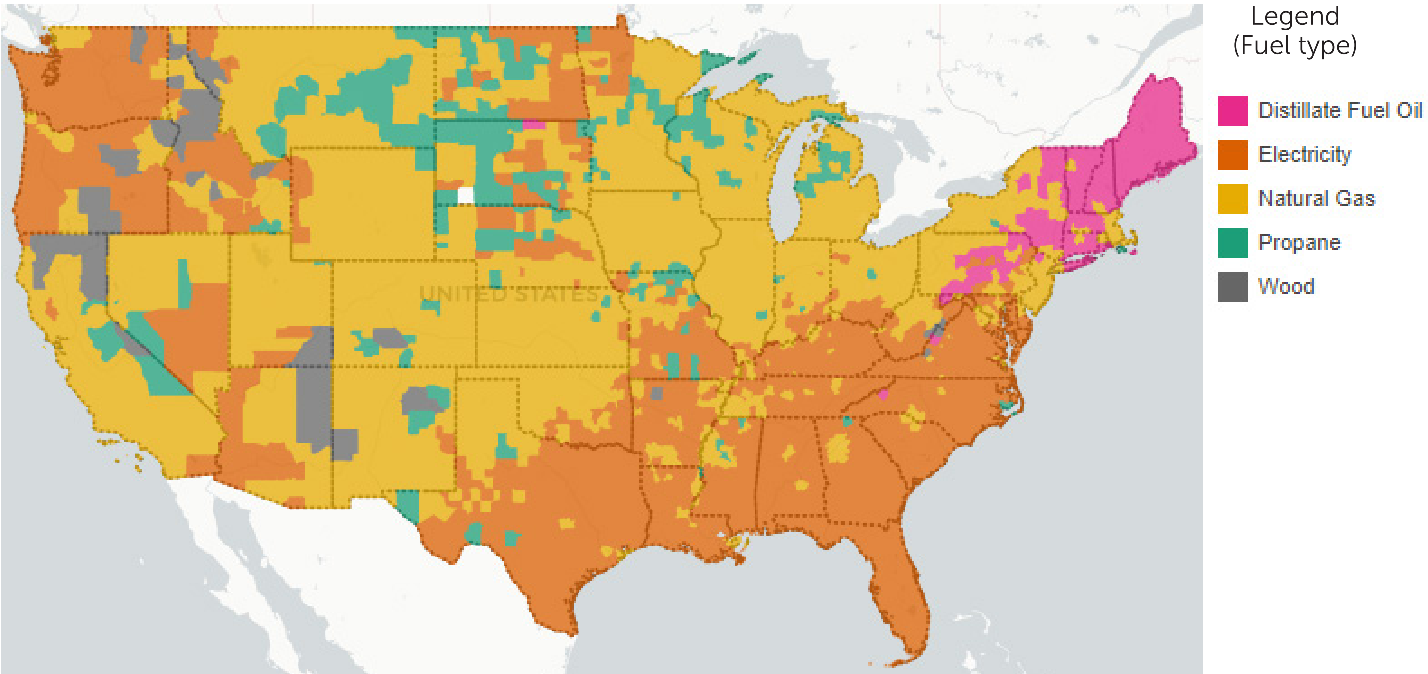

Figure 10: *Dominant Fuel Type, Source – NREL*

This contrast explains some of the variations in energy burdens across the country. Additionally, this paper identifies the impact of climate change on energy burden susceptibility in the US. This analysis shows that extreme physical weather conditions raise the need for cooling, especially in the south, which is also characterized by a low housing inventory of new construction homes compared to older homes, (shown in the figure below) which as stated earlier, can be a major contributor to high energy costs.

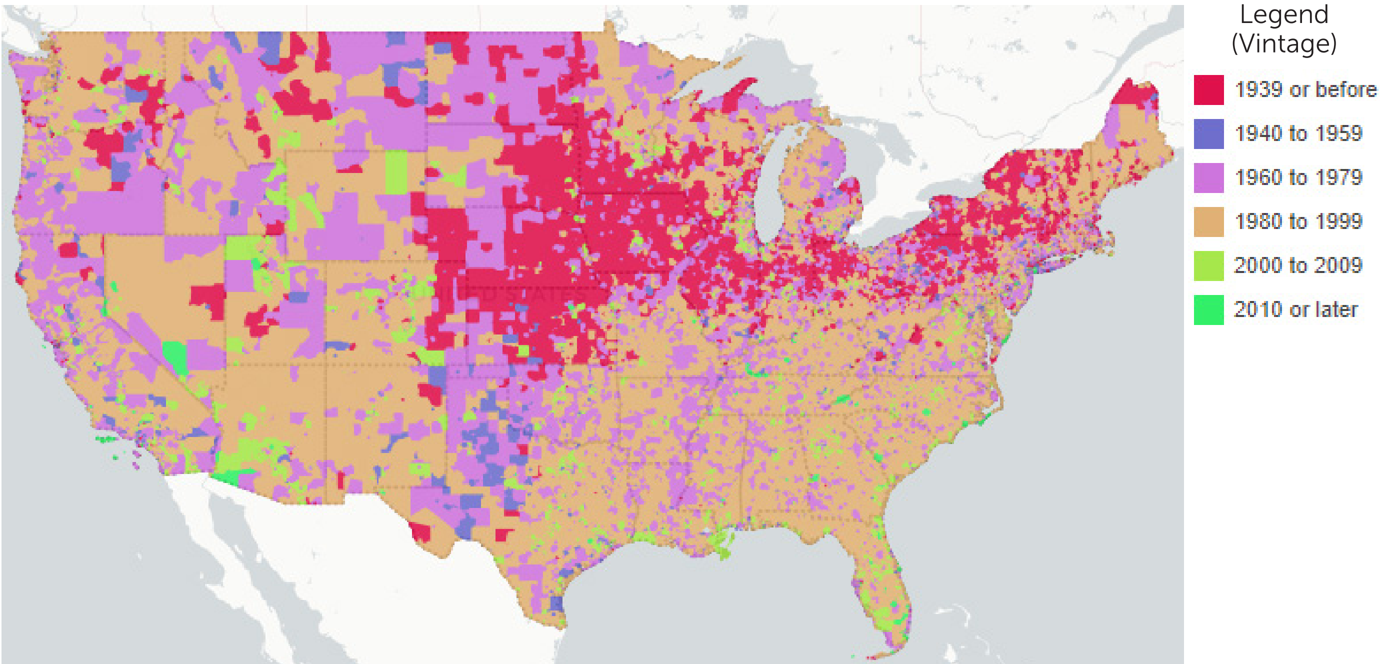

Figure 11: *Number of Housing Units by Vintage (Housing stocks,- Source – NREL*

The conclusions derived from this paper show that utility bills present a threat to the affordability of residential housing in the US. From a policy perspective, low-income households are not able to meet their monthly obligations due to high energy upfront costs, which are not applied evenly to all customers based on income levels by the utilities. Energy burdens can be reduced if utilities developed a framework where fixed charges are determined based on income. This study determines that weatherization is necessary, but it is not a sufficient approach to address structural deficiencies in housing facing LMI households. By implication, energy efficiency programs focusing on LMI households should anticipate and address potential structural challenges in the housing itself. This study shows that energy burden has the tendency of precluding low-income households from enjoying sustainable long-term economic growth. As a result, this study recommends that energy efficiency and assistance programs aimed at low-income households be prioritized as high monthly bills suggest energy conservation programs. The paper can be further extended to include the impact of heating and cooling degree days on the energy burdens for each state.

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Appendix A: *Energy Burden Landscape in the U.S.*

State Abbreviation	LMI Energy Burden	Non-LMI Energy Burden
AL	20.87%	7.20%
AK	42.35%	24.50%
AZ	16.19%	6.16%
AR	18.90%	7.29%
CA	6.87%	3.83%
CO	7.77%	3.75%
CT	18.49%	14.88%
DC	7.08%	1.77%
DE	13.45%	7.48%
FL	11.40%	5.17%
GA	19.40%	6.87%
HI	23.11%	6.36%
IA	6.61%	4.29%
ID	11.72%	6.86%
IL	7.20%	4.06%
IN	8.82%	5.78%
KS	6.89%	4.57%
KY	19.11%	6.22%
LA	13.18%	4.36%
MA	15.63%	10.52%
MD	11.91%	6.51%
ME	40.36%	28.05%
MI	14.49%	7.50%
MN	9.04%	5.87%
MO	14.06%	6.28%
MS	26.66%	8.28%
MT	9.85%	5.33%
NC	19.80%	7.74%
NE	7.80%	4.75%
NV	7.86%	5.31%
NH	19.68%	16.80%
NJ	8.35%	5.96%
NM	15.23%	5.27%
NY	16.26%	10.88%
ND	10.32%	4.79%
OH	10.00%	6.30%
OK	10.54%	4.81%

OR	11.07%	6.31%
PA	18.67%	12.34%
RI	19.36%	15.98%
SC	22.02%	7.32%
SD	11.61%	5.63%
TN	14.60%	6.27%
TX	9.21%	4.36%
UT	6.30%	3.34%
VT	27.15%	19.34%
VA	14.16%	6.40%
WA	7.31%	4.27%
WV	17.79%	7.01%
WI	8.99%	5.84%
WY	5.60%	3.89%

Source: Derived by averaging energy burdens at the county level for each state from the NREL data

Appendix B: *Energy Burden Indicators*

State	Outcome Var.	Unemp. Rate	Poverty Rate	Median HhInc	Median Gross Rent	Avg Monthly Bill	Dlrs Kwh
DE	1	5.8	11.3	68287	1130	125.6195	0.133163
GA	1	4	13.3	58700	1006	131.6603	0.117018
NV	0	7.8	12.5	60365	1107	103.808	0.112881
VA	1	4.3	9.9	74222	1234	127.1873	0.113607
MI	1	5	13	57144	871	102.7037	0.154554
NC	1	4.6	13.6	54602	907	118.8318	0.107469
IN	0	4.1	11.9	56303	826	119.0533	0.12053
SC	1	4.5	13.8	53199	894	150.2142	0.127719
NM	1	7.9	18.2	49754	844	75.82394	0.124327
MS	1	6.2	19.6	45081	780	124.387	0.105004
OK	1	3.7	15.2	52919	810	112.4263	0.101948
CO	0	6.2	9.3	72331	1271	83.79528	0.120711
OH	1	5.2	13.1	56602	808	107.2368	0.123971
MO	1	4.3	12.9	55461	830	119.0312	0.115323
FL	1	5	12.7	55660	1175	124.0777	0.110032
WV	1	5.3	16	46711	725	117.064	0.116626
PA	1	6.9	12	61744	938	107.8407	0.134965
RI	1	5.9	10.8	67167	1004	107.27	0.185074
KS	0	3.7	11.4	59597	850	120.8755	0.132678
WI	0	3.9	10.4	61747	856	97.6826	0.143658
NE	0	2.5	9.9	61439	833	120.3394	0.108495

IA	0	4	11.2	60523	789	116.7207	0.118242
MA	1	4.9	9.4	81215	1282	108.8158	0.190066
OR	1	5.6	11.4	62818	1110	97.44264	0.109228
AL	1	3.3	15.5	50536	792	148.804	0.124673
ME	1	4.8	10.9	57918	853	82.024	0.152973
IL	0	7.2	11.5	65886	1010	79.77595	0.11717
MN	0	4	9	71306	977	105.3457	0.130004
UT	0	2.7	8.9	71621	1037	82.66082	0.112149
MT	0	3.7	12.6	54970	810	93.53178	0.111576
AK	1	6.6	10.1	77640	1244	120.2058	0.213725
AZ	1	6.8	13.5	58945	1052	121.6949	0.120096
AR	1	4.4	16.2	47597	745	108.6546	0.100438
CA	0	7.7	11.8	75235	1503	93.00101	0.173975
CT	1	7.9	10	78444	1180	132.5443	0.197316
HI	1	7.7	9.3	81275	1617	131.9275	0.272346
ID	1	3	11.2	55785	853	94.99037	0.101474
KY	1	4.4	16.3	50589	763	118.3682	0.105356
LA	1	6.9	19	49469	866	116.2247	0.094789
MD	1	6.2	9	84805	1392	136.0829	0.141662
NH	1	2.9	7.3	76768	1111	110.5135	0.186657
NJ	0	7.3	9.2	82545	1334	104.9825	0.157526
NY	1	7.7	13	68486	1280	98.9519	0.194211
ND	1	4	10.6	64894	826	120.2189	0.1028
SD	1	2.9	11.9	58275	747	129.8474	0.118422
TN	1	4.9	13.9	53320	869	128.8229	0.104124
TX	0	6.5	13.6	61874	1045	121.7275	0.108579
VT	1	3.1	10.2	61973	985	95.18822	0.175133
WA	0	5.2	9.8	73775	1258	91.45512	0.097015
WY	0	5.4	10.1	64049	855	96.1839303	0.11944

Appendix C: *Housing Indicators and Control Variables.*

State	Rent burden	%AfrAm	%Asian	%Hisp	Persons phh	Housing units	Building permits	Pop.
DE	19.8573667	23.2	4.1	9.6	2.57	443781	8455	973764
GA	20.56558773	32.6	4.4	9.9	2.7	4378391	55827	10617423
NV	22.00612938	10.3	8.7	29.2	2.67	1285684	19716	3080156
VA	19.95095794	19.9	6.9	9.8	2.61	3562143	33813	8535519
MI	18.29063419	14.1	3.4	5.3	2.47	4629611	19735	9986857
NC	19.93333578	22.2	3.2	9.8	2.52	4747943	80474	10488084
IN	17.60474575	9.9	2.6	7.3	2.52	2921032	24919	6732291
SC	20.16579259	27	1.8	6	2.54	2351286	42340	5148714
NM	20.35615227	2.6	1.8	49.3	2.63	948473	5219	2096829
MS	20.76262727	37.8	1.1	3.4	2.62	1339021	7810	2976149
OK	18.36769402	7.8	2.4	11.1	2.58	1749464	13733	3956971
CO	21.08639449	4.6	3.5	21.8	2.56	2464164	40469	5759736
OH	17.13013674	13.1	2.5	4	2.43	4676358	29686	11689100
MO	17.95856548	11.8	2.2	4.4	2.46	2414521	19839	6137428
FL	25.33237513	16.9	3	26.4	2.65	7736311	164074	21477737
WV	18.62516324	3.6	0.8	1.7	2.42	732585	3204	1792147
PA	18.23011143	12	3.8	7.8	2.45	5053106	25706	12801989
RI	17.93737996	8.5	3.7	16.3	2.47	410489	1374	1059361
KS	17.11495545	6.1	3.2	12.2	2.51	1288401	8211	2913314
WI	16.63562602	6.7	3	7.1	2.39	2725296	21226	5822434
NE	16.26979606	5.2	2.7	11.4	2.45	851227	9483	1934408
IA	15.64363961	4.1	2.7	6.3	2.4	1418626	12623	3155070
MA	18.94231361	9	7.2	12.4	2.52	2928732	17025	6892503
OR	21.20411347	2.2	4.9	13.4	2.51	1808465	18665	4217737
AL	18.80639544	26.8	1.5	4.6	2.55	2284847	19982	4903185
ME	17.6732622	1.7	1.3	1.8	2.32	750939	5304	1344212
IL	18.39541025	14.6	5.9	17.5	2.57	5388066	18058	12671821
MN	16.44181415	7	5.2	5.6	2.49	2477753	28148	5639632
UT	17.37479231	1.5	2.7	14.4	3.12	1133521	31775	3205958
MT	17.6823722	0.6	0.9	4.1	2.39	519935	5980	1068778
AK	19.22720247	3.7	6.5	7.3	2.8	319854	1420	731545
AZ	21.41657477	5.2	3.7	31.7	2.68	3075981	60342	7278717
AR	18.78269639	15.7	1.7	7.8	2.52	1389129	12493	3017804
CA	23.97288496	6.5	15.5	39.4	2.95	14366336	106075	39512223
CT	18.05109377	12.2	5	16.9	2.53	1524992	5471	3565287
HI	23.87450015	2.2	37.6	10.7	3	550273	3164	1415872
ID	18.34901855	0.9	1.6	12.8	2.68	751105	19130	1787065
KY	18.09879618	8.5	1.6	3.9	2.49	2006358	11281	4467673
LA	21.00709535	32.8	1.8	5.3	2.61	2089777	17283	4648794

MD	19.69695183	31.1	6.7	10.6	2.67	2470316	17982	6045680
NH	17.36661109	1.8	3	4	2.46	64315	4320	1359711
NJ	19.39305833	15.1	10	20.9	2.69	3641812	36146	8882190
NY	22.42794148	17.6	9	19.3	2.59	8404381	37330	19453561
ND	15.27413937	3.4	1.7	4.1	2.3	380173	3493	762062
SD	15.38223938	2.3	1.5	4.2	2.43	401862	6600	884659
TN	19.55738935	17.1	2	5.7	2.52	3028213	49719	6829174
TX	20.26699421	12.9	5.2	39.7	2.85	11283353	230503	28995881
VT	19.07282204	1.4	1.9	2	2.3	339439	2077	623989
WA	20.4622162	4.4	9.6	13	2.55	3195004	43881	7614893
WY	16.01898546	1.3	1.1	10.1	2.46	280291	2128	578759

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