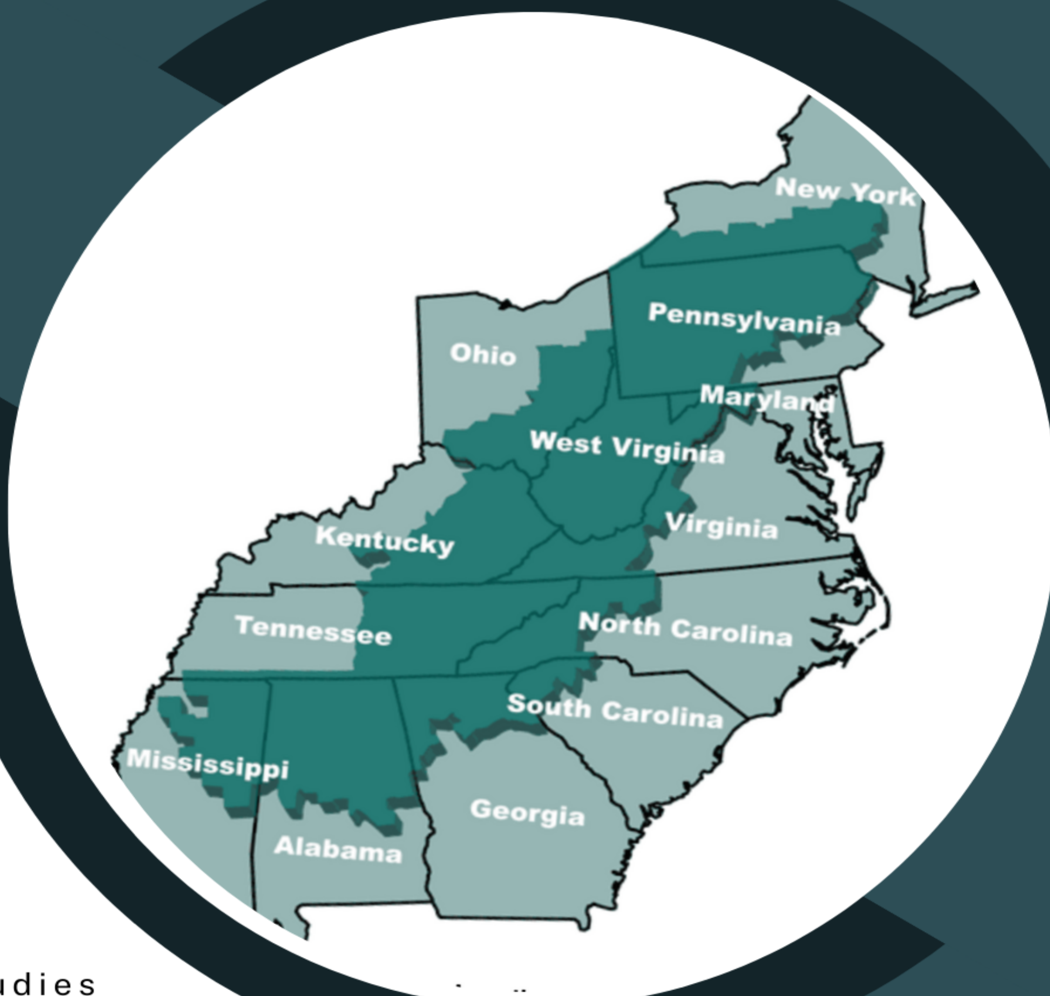
Masters Thesis

TO HEAT OR TO EAT?

ASSESSING ENERGY POVERTY IN THE APPALACHIAN REGION OF THE UNITED STATES



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July 2024

Masters Climate Studies
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Master Thesis

To Heat or to Eat? Assessing Energy Poverty in the Appalachian Region of the United States

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Abstract

This thesis investigates energy poverty in the Appalachian region of the United States, an area historically characterized by economic distress and dependency on the declining coal industry. It addresses the spatial distribution across the region by assessing how energy poverty varies using single measures such as the greater than 10% (>10%) and Twice the National Median (Mx2), as well as composite indices through Hidden Energy Poverty (HEP). A narrative literature review provides the background for identifying indicators of energy poverty, which are then explored through a LISA in GeoDa using data from the U.S. Energy Information Administration's 2020 Residential Energy Consumption Survey (RECS). Two logit regression models that employ the different indicators of fuel poverty are used to explicate the household traits influencing energy poverty. The findings highlight the complexity and difficulty in measuring energy poverty in the US context, while providing new empirical data on its spatial distribution, as well as insights into the relevance of educational attainment, race, age, and work in energy poverty. The conclusion highlights the value of the study, while outlining how further research is needed on energy poverty in Appalachia and across the US to adequately support policymakers.

1. Introduction

The Universal Declaration for Human Rights, article 25, outlines that "everyone has the right to a standard of living adequate for the health and well-being of himself and of his family, including food, clothing, housing and medical care" (United Nations, 1948, art. 21.3). Actualizing these rights is an immense societal and geopolitical challenge which is further complicated as our world reaches its planetary boundaries (Rockström et al., 2009). The vulnerable communities who have contributed the least towards climate change are disproportionately impacted by it (IPCC, 2023). One key area where the risks and benefits of sustainable transitions are most clearly unjust for vulnerable communities is within the energy transition (Sareen & Haarstad, 2018; Carley & Konisky, 2020), as increased fuel prices impact low-income households the most (Brown et al., 2021).

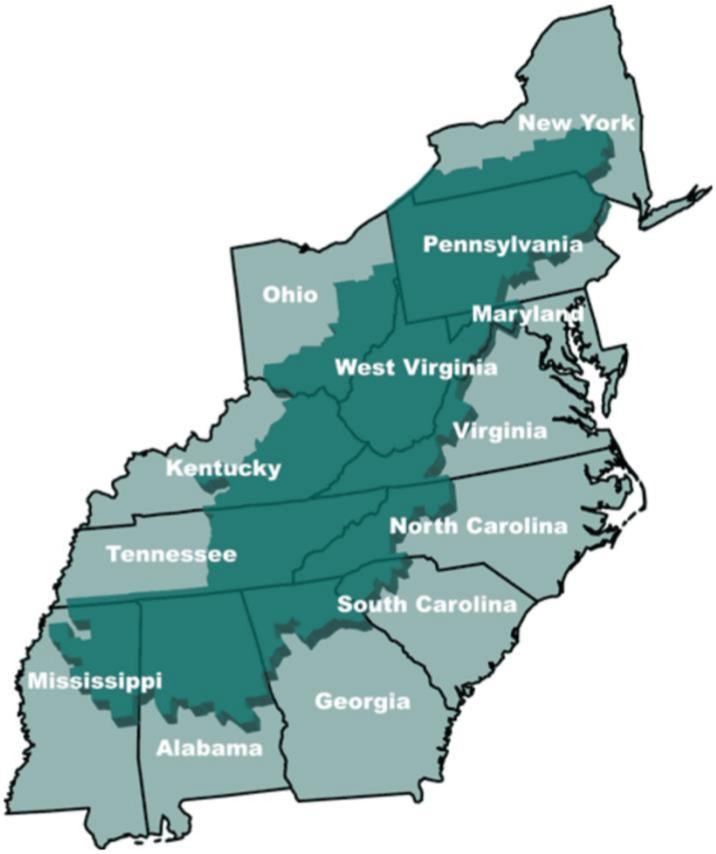
As weather events become more extreme the need for energy will increase and change (Hills, 2011). The vulnerable communities, both within and between countries, which face daily hardships are also those vulnerable to the impacts of climate events (Jessel et al., 2019). Wisner et al. (2006) point out that disparity worsens with repeated shocks from changes in climate. Poverty is intricately linked to energy poverty due to its impact on access to basic energy services, as impoverished individuals often struggle to afford reliable and sustainable energy sources, exacerbating their socioeconomic challenges (Doukas & Marinakis, 2020; González-Eguino, 2015).

The complexity of energy poverty (Baker et al., 2018) is motivated by varied socioeconomic factors (Kearns et al., 2019; Namazkhan et al., 2020) and spatial factors (Bouzarovski and Simcock, 2017; Mashhoodi, 2020). Energy poverty definitions are numerous and recommendations of which indicators to use are diverse. Energy poverty can be broadly defined within the global minority (global north) as the inadequate (inability to) access to affordable and reliable energy services (Boardman, 2013; Hills, 2012; HM government, 2015; Thomson et al., 2016), and some further include in the definition e.g., social and material needs to live within a context (Bouzarovski, 2018), key dimensions of economic, physical and behavioral (Hernández, 2016). Alongside formally recognizing energy poverty, the decision of how to measure, the development of a measurement framework, data collection or policy recognition are ways forward (Bednar and Reames, 2020). Further, energy poverty indicators are wide ranging in variables and measures included with the potential for policy prioritization dependent on something as arbitrary as the indicator used. Countries, such as the United States (U.S.), and particularly impacted regions like Appalachia, do not differentiate energy poverty from general poverty (Bednar and Reames, 2020) even though the connections between income poverty and energy poverty are strong (Dalla Longa, et al., 2021).

The nexus between energy poverty and climate change underscores a critical intersectionality within the U.S., particularly concerning its spatial distribution and environmental ramifications. In the U.S. despite being one of the world's wealthiest nations, energy poverty remains a persistent issue with significant social, economic, and environmental implications (Hernandez, 2013; Brown et al., 2021). Energy poverty exacerbates the vulnerability of marginalized communities to the adverse impacts of climate change, perpetuating a cycle of environmental injustice (Jessel et al., 2019). Moreover, the wealth disparity in the U.S. is growing which will exacerbate those at risk or already experiencing energy poverty (Kontokosta et al., 2020). Understanding the variations in energy poverty across different populations and regions is essential for developing targeted interventions and policies to address this pressing issue (Bouzarovski, 2018; Middlemiss, 2020; Simson, 2023). To achieve this, more research is needed on energy poverty in the U.S. through assessing different indicator results and how these differ across states and regions (Agbim et al., 2020; Wang et al, 2021; Cong et al., 2022).

Within the U.S., the Appalachian Region (Figure 1) has historically been characterized by deep poverty, with county poverty rates over 40% in 1960, about double the national average at the time (Partridge et al., 2013). While the poverty gap has narrowed, it remained nearly twice as large in Central Appalachia as of 1990. As of 2020, close to half the counties in Northern, North Central, and Central Appalachia (covering parts of PA, OH, WV, and KY) were classified as economically "distressed" or "at-risk" by the Appalachian Regional Commission based on unemployment, income, and poverty rates (Department of Energy, 2020; Pollard et al., 2024). Coal mining, a major industry in the Appalachian region, has been linked to higher poverty rates. Studies suggest coal mining's impact on poverty may be due to factors like weaker entrepreneurship, lower educational attainment, environmental degradation, and limitations on other economic opportunities - aspects of the "natural resource curse" (Partridge et al., 2012; Lobao et al., 2020). While poverty has improved over time, the Appalachian region, especially coal-dependent areas, still lags behind the rest of the nation economically and faces higher risks of energy poverty due to its historic reliance on the declining coal industry (Lobao et al., 2020).

Figure 1: Appalachian region of the U.S.



Source: Appalachian Regional Commission

To date, no study has assessed energy poverty specifically in the Appalachian region separately from general poverty. While research has focused on the energy transition in the region (Pollard, 2023) via the decline of the coal industry (Partridge et al., 2013; Hess et al., 2021) or the feasibility of a clean energy transition (Chen et al., 2024; Harris and McCarthy, 2021; Carley et al., 2020), none have investigated energy poverty specifically.

Due to the general complexity of poverty, and more particularly, energy poverty (Che et al., 2021), the extent and spatial distribution of energy poverty in Appalachia may be dependent upon which definition is used.

1.1 Thesis Objective

This study aims to analyze academic literature for potential ways to assess energy poverty in the region of Appalachia in the U.S. We utilize this literature to identify indicators of energy poverty to analyze the U.S. Energy Information Administration's 2020 federal survey on Residential Energy Consumption (RECS) specific to the region of Appalachia in the U.S. This thesis's objective is to assess how energy poverty in the U.S. region of Appalachia varies using different indicators of it. A comparison of the different measures is done via statistical analysis and spatial assessment

The research objective is operationalized in a set of research questions:

1. What are the different indicators of energy poverty used in the literature, and specifically in U.S. studies? (RQ1)
2. How are various energy poverty indicators distributed spatially in the Appalachian region? (RQ2)
3. What household traits are associated with various energy poverty indicators across the Appalachian region? (RQ3)

The remainder of this thesis is structured as follows. Section 2 provides a review of relevant academic and gray literature on energy poverty in the United States and methodologies to measure energy poverty. Section 3 provides an overview of the methodologies to be used. Section 4 presents the results of the statistical and spatial analyses. Section 5 discusses the results. Recommendations and conclusions are shared in Section 6.

2. Background of Energy Poverty in the United States

To heat or to eat? That is the question (Frank et al., 2006). The choice between heating one's home and feeding one's family is a stark reality for millions of Americans who may be experiencing energy poverty. This issue, which is both growing and poorly defined, highlights the critical intersection of basic needs and socio-economic vulnerability. Building on the energy insecurity framework (Hernandez, 2013), this review explores household energy poverty within the context of a just and sustainable energy transition to highlight the disproportionate burdens borne by vulnerable populations in adequately meeting household energy needs in the U.S., and specifically in the Appalachian region.

2.1 Methodology of Literature Review

The identified academic literature was found via the database SCOPUS through a search strategy that uses keywords for the titles of articles, their abstracts, and their key words. This approach aimed to ensure that the search results were more comprehensive and relevant by considering multiple aspects of the article’s metadata. The search strings used included terms related to “Energy Poverty" and "Spatial Analysis" detailed in Table 1. These search strings were useful because they covered different terminology relevant to the U.S. context (e.g., energy poverty, vulnerability, insecurity, burden), ensured comprehensiveness by including spatial analysis and related geographic terms, and captured studies at various scales (e.g., local, regional, urban) and used different methods (e.g., GIS, geographic analysis). By using these search strings, one can gather a broad and detailed understanding of how energy poverty is measured and analyzed spatially in the U.S.

Table 1: Summary of search strings, its relevance to this research and what specific aspects or methods it focuses on in the context of energy poverty research in the U.S.

Search String	***Relevance***	***Focus***
"Energy Poverty" AND "Spatial Analysis"	Targets studies and discussions focusing on the concept of energy poverty and its geographic distribution.	Ensures inclusion of research applying spatial analysis techniques to understand energy poverty.
"Energy Vulnerab" AND ("Spatial Analysis" OR geographic OR GIS OR local OR regional OR urban)**	Broadens the scope to include factors contributing to a household's susceptibility to energy poverty.	Captures diverse methods and scales of spatial analysis, offering a thorough examination of energy vulnerability.
"Energy insecurity" AND ("spatial analysis" OR geographic OR GIS OR local OR regional OR urban)	Highlights the lack of reliable and affordable energy access, impacting health and economic stability.	Ensures comprehensive coverage of different spatial contexts and analysis techniques.

The search terms were identified from foundational literature on energy poverty and grouped into synonym lists to create inclusive searches. Some search phrases were excluded, such as "Fuel Poverty", more commonly used in the UK than the US. As the research is US-focused, this term is less necessary. The documents were assessed for duplicates prior to analysis and the literature list was complemented by snowballing to identify additional publications. Identified publications were screened for relevance based on their abstracts. If found it to be relevant, the source was read in-depth and used to develop the initial assessment of energy poverty in the United States.

2.2 Energy Poverty in the United States

Existing data shows that more than 5.2 million households above the Federal Poverty Line face energy poverty (Bednar & Reames, 2020). Households below the poverty line face an even greater risk of energy poverty, as they often have limited financial resources to cover their energy costs with broader impacts intertwined with numerous vulnerabilities related to poverty (Hernandez, 2013). With one in three U.S. households experiencing energy poverty (RECS, 2015) and the U.S. federal government still not formally recognizing it (Bednar and Reames, 2020), there remains a need to address energy poverty theoretically and practically (Jenkins, et al., 2017; Kontokosta et al., 2020; Jones and Reyes, 2023).

There is no agreed upon definition of energy poverty in the U.S. nor a metric to measure it (Teller-Elsberg et al., 2016; Bednar & Reames, 2020). Clear definitions for affordability, poverty, and vulnerability are crucial for effective policymaking and addressing social welfare concerns (Kessides et al., 2009; Lin, 2018). The interchanging use of these terms in the U.S. context reflects the lack of policy focus on creating substantial change and makes it challenging to compare research findings and knowledge gained (Bednar and Reames, 2020). There are several terms used to discuss energy poverty experienced by low-income households in the U.S. such as: energy burden, energy access, fuel poverty, energy affordability, energy insecurity, and energy poor. By agreeing to a single term and enshrining it into policy documents and national level data collection, the U.S. could more effectively target the impacts of energy poverty (Bednar and Reames, 2020).

Beyond a common definition, there are various indicators used to assess energy poverty with no consensus as to which is most robust in capturing the multidimensionality of energy poverty (Boardman, 2013; Hills, 2012; Bouzarovski, 2014; Schuessler, 2014; Bouzarovski and Petrova, 2015). Looking to Europe, where energy poverty has been formally recognized, and the literature more refined, an expenditure-to-income ratio for energy expenditure remains the most used measure (Bouzarovski, 2018). Expenditure-to-income ratio indicators have faced extensive criticism from various scholars, including Healy and Clinch (2004), Harrison and Popke (2011), Hills (2012), and Bouzarovski (2014). Critics point to the missing inclusion of spatial and temporal factors or differences in types of energy poverty (Liddell et al., 2012). Energy poverty households' ability to afford energy bills, the percentage of household income spent on energy, and the presence of energy-related hardships, such as inadequate heating or cooling, can be used to measure energy poverty (Bednar & Reames, 2020). Additional factors influencing energy poverty can include appropriate design of homes, local climate conditions, local energy market conditions, and the availability of assistance programs for the population (Liu and Judd, 2019). Fizaine and Kahouli

(2019) conclude that the attributes of populations classified as energy poor vary based on the metric used to assess energy poverty.

Energy poverty was initially documented as a matter of affordability, access to energy, and encompasses the quality and (in)efficiency of energy services in households (Boardman, 1991; Buzar, 2007; Hernández and Bird, 2010). For instance, households that are trapped in housing arrangements and heating systems that are costly and inefficient are more likely to experience energy poverty (Bouzarovski, 2014). There is evidence to suggest that awareness of climate change issues plays a role in driving energy-related renovations in low-income households (Belaid and Massie, 2023). Drehobl and Ross (2016) also note the divide between owners and renters, with owners less likely to be impacted than renters by energy poverty. Such a division is further deepened by the reduced inclusion of renters in energy efficiency programs from utility companies (Drehobl and Ross, 2016).

Additionally, socio-demographic characteristics such as race, employment, marital status, and education are tied to energy poverty due to financial hardship and social vulnerability (Bouzarovski, 2014; Bouzarovski and Simcock, 2017). Bednar and Reames (2020) call for a comprehensive response to address energy poverty, including recognizing it as a distinct problem from general poverty, implementing targeted assistance programs, and addressing systemic inequities in energy access.

Inability to adequately heat homes, afford energy bills, or access modern energy services can lead to respiratory illnesses, cardiovascular diseases, poor mental health, and other adverse health effects (Brown and Vera-Toscano, 2021; Champagne et al., 2023; Bentley et al., 2023). There is a bidirectional relationship between energy poverty and health (Brown and Vera-Toscano, 2021). While energy deprivation negatively impacts health, poor health can also increase vulnerability to energy poverty by reducing income and increasing energy needs (e.g., for medical equipment) (Brown and Vera-Toscano, 2021). Incorporating health indicators is crucial for fully capturing the detrimental effects of energy poverty, understanding its complex interplay with well-being, and designing effective policies to alleviate this form of deprivation and its health burdens on vulnerable populations (Brown and Vera-Toscano, 2021; Lei et al., 2021; Champagne et al., 2023; Bentley et al., 2023). Beyond physical health, energy poverty has direct impacts on mental health outcomes as well, as evidenced by Brown and Vera-Toscano (2021), Lei et al. (2021), Champagne et al. (2023) and Bentley et al. (2023).

The U.S. does not take a unified approach due to the structure of federal funding programs (Charlier and Legendre, 2021; Bednar and Reames, 2020). Few studies have been conducted in the U.S. to account for variations in contextual variables between individuals from different geographic regions, as much of the literature is based on research conducted in Europe (Bednar and Reames, 2020). Moreover, the gravity of the repercussions of energy poverty, as perceived and reported by residents (e.g., in surveys like RECS), highlights the need to broaden our knowledge of energy poverty in various geographic locations and how that knowledge may be used to make recommendations for policies and programs.

2.3 Existing Policy Landscape of Energy Poverty in the United States

The current policies developed to address energy poverty in the U.S. at the federal level are reliant on performance indicators tied to the number of households assisted. Importantly, the U.S. federal government does not explicitly recognize energy poverty (Bednar and Reames, 2020). The U.S. addresses energy poverty and promotes energy affordability mainly through two federally funded initiatives: the Low Income Home Energy Assistance Program (LIHEAP) and the Weatherization Assistance Program (WAP) (Bednar and Reames, 2020). At the federal level, LIHEAP provides financial assistance to low-income households to help cover heating and cooling costs with funding through the U.S. Department of Health and Human Services. It is administered by states, with the goal of ensuring that vulnerable populations have access to essential energy services. There have been efforts to increase energy efficiency in low-income households through programs such as WAP funded through the U.S. Department of Energy. WAP helps eligible households improve energy efficiency by providing funding for insulation, weather-stripping, and other measures to reduce energy consumption and lower utility bills.

Crucially, the short-term design of existing federal policies, such as LIHEAP, do not address the root cause of energy poverty nor mitigate the inadequate housing of those affected (Hernandez and Bird, 2010). Additionally, the distribution of federal funds for LIHEAP to the state-level is unequal with states primarily using heating receiving more funding than those needing energy for cooling (Perl, 2015; Agbim et al., 2020). Existing programs offer crucial aid to disadvantaged households, yet their measurement and assessment criteria concentrate chiefly on resource allocation and servicing a target number of households, rather than on enhancing overall household welfare and alleviating energy poverty (Bednar and Reames, 2020). As Brown et al. (2020) observe, the patchwork of energy policies in the U.S. "do not target the needs of low-income households" (p. 7). The needs of low-income households refer to the affordability and accessibility of energy policies and programs, which are often out of reach for them due to high up-front costs and insufficient tax liabilities. The congressional funding appropriations expose the primary response and disproportionate support that LIHEAP historically receives compared to WAP and exemplifies the disparity in investments of federal resources aimed at responding to energy poverty, despite LIHEAP's design as a short-term solution (Hernandez and Bird, 2010).

Notable beyond the federal policies, certain states and localities within the U.S. have implemented utility assistance programs[1], rate assistance programs, and energy efficiency incentives[2] (Drehobl and Castro-Alvarez, 2017; York et al., 2020). Some programs specifically target low-income communities to alleviate energy burden and promote energy equity (Drehobl and Castro-Alvarez, 2017). Such policies reflect a broader recognition of the importance of addressing energy poverty as part of efforts to promote social equity, economic stability, and environmental sustainability (Pauchari et al., 2013; Bednar and Reames, 2020). However, without formal and comprehensive recognition of energy poverty at the federal level, the effectiveness of current responses is masked by performance measures not aligned with national energy poverty reduction (Bednar and Reames, 2020). These observations suggest that currently U.S. policies are inadequate.

2.4 Energy Poverty Knowledge Gaps for the United States and Appalachian Region

Most of the literature currently in publication is based on research conducted in Europe which highlights the need to broaden our knowledge of energy poverty in other geographic locations. Nevertheless, few studies have been conducted in the U.S. to account for variations in contextual variables between individuals from different geographic regions (Mohr, 2018). Research to date has demonstrated the critical roles that sociodemographic characteristics, household composition,

[1] https://liheapch.acf.hhs.gov/Supplements/suppintro.htm

[2] Subramanian, S., W. Berg, E. Cooper, M. Waite, B. Jennings, A. Hoffmeister, and B. Fadie. 2022. 2022 State Energy Efficiency Scorecard. Washington, DC: ACEEE. www.aceee.org/research-report/u2206.

and health play in the causes and effects of energy poverty (Bouzarovski, 2014; Bouzarovski and Simcock, 2017).

Furthermore, there have been calls for more holistic energy poverty indicators to include considerations of housing conditions adequacy (Cong et al., 2022; Alkire et al., 2013), reliability, affordability of household energy supply, along with the coping strategies employed by households to manage energy-related challenges (Sovacool et al., 2017; Carley et al., 2020) even extending to energy efficiency, and renewable energy adoption (Lucon et al., 2014). How that knowledge may and/or should be used to make (more inclusive) recommendations for policies and programs is at times included but is not mainstreamed within the literature.

Poverty itself varies spatially due to a breadth of variables; but when trying to capture it through different indicators, different distributions are found (Curtis et al., 2019). Further, data availability to support different, multifaceted indicators is also noted as limited but can provide data to identify who or where may be in need (Curtis et al., 2019).

Within the U.S. energy poverty literature, there is an even greater gap in the understanding of Appalachia, despite its relevance for research in this area due to its longstanding socio-economic vulnerability as a region (Partridge et al., 2013; Department of Energy, 2020) alongside its embedded position with the energy production system of the U.S. (Curtis et al., 2019; Lobao et al., 2016).

3. Methodology

The methodologies used in the following research are divided into three research questions. Section 3.1 presents the methods employed to identify the energy poverty indicators from the literature review, which informed the specific indicators used in Section 3.2 and 3.3. Section 3.2 details the methods used for assessing spatial distribution of the energy indicators identified and Section 3.3 outlines the methods followed to assess the household traits associated with the indicators.

3.1 Identifying Indicators of Energy Poverty

The first research question is addressed through a narrative literature review of academic publications and gray literature focusing on the topics of energy poverty and spatial analysis. This was important to the thesis due to the limited research in this area in the Appalachian region.

Further, the approaches selected in Section 3.2 and 3.3 implement the indicators identified and selected through the literature review.

3.2 Assessing the Spatial Distribution of the Respective Indicators

Through the literature review, the 2020 Residential Energy Consumption Survey (RECS), was identified as the primary dataset for measuring the spatial distribution and characteristics of the different indicators of energy poverty. The dataset is extensive, containing over 600 variables that provide detailed insights into household energy characteristics, consumption, and expenditures across the U.S. (EIA, 2020). Since 1978, the Residential Energy Consumption Survey (RECS) is the sole nationwide source for energy-related characteristics, consumption, and expenditures in U.S. homes. It is a multi-phase study that starts with a household survey, gathering information on the physical attributes of the home and energy use behaviors. The Energy Information Administration (EIA) then contacts the household's energy suppliers to collect data on fuel consumption and expenditures. The 2020 RECS is the fifteenth iteration of the survey, done every five years (EIA, 2020).

The data was collected from 18,500 households across all 50 states and the District of Columbia (EIA, 2020). This marked the first-time state-level data was available for all states and the District of Columbia. Owners and renters are considered separately because they differ between income profiles (Mohr, 2018). The RECS 2020 survey reports gross household income in sixteen intervals. The midpoint of the income decile for the household is used in Table 4. This lack of precision is partially compensated by having the low-income marker set at the federal poverty level for a family of four at $31,200 (U.S. Department of Health and Human Services, 2024).

Energy poverty is a critical issue for lower-income households, affecting both homeowners and renters, though renters might face slightly higher risks due to factors like property conditions and lease terms. However, due to the aforementioned “split incentive,” only homeowners were included in the data analysis.

The approach to determine the spatial distribution of energy poverty, specifically for the 13 states of the Appalachian region of the US, focused on a Local Indicators of Spatial Association (or Autocorrelation) method (LISA). The application of LISA has become increasingly popular in the natural sciences for statistically quantifying spatial patterns (Anselin, 1995; Eamer and Walker, 2013; Nelson and Boots, 2005; Nelson and Boots, 2008; Das Majumdar and Biswas, 2016). Local Moran's I statistics can show "positive and negative spatial autocorrelation based on the attribute value of a location relative to its neighbors" (Das Majumdar and Biswas, 2016, p. 52). While global measures of spatial autocorrelation, such as Moran's I and Geary's c, assess overall clustering in a dataset by providing an average value, LISA characterizes spatial autocorrelation at a local level, identifying spatial distribution and spatial outliers that deviate significantly from the mean (Anselin, 1995). Therefore, a LISA was chosen as a relevant method.

Conducting a LISA in GeoDa (overview in Table 2) involves defining the study area, constructing a spatial weights matrix, calculating spatial autocorrelation, computing local Moran's I statistics, assessing their significance, and visualizing the results to identify significant spatial patterns. The area was defined based on the Appalachian Regional Commission's geographic definition of the Appalachian Region, including 13 states (see in Figure 1). The RECS data relevant to the 13 states was extracted and is available at the state level for the first time in the 2020 survey used in the research. Initially, the available shape file, required for GeoDa, included 24 states. QGIS was used to create a new shape file containing only the relevant geographic area of 13 states.

Table 2: GeoDa LISA methodology

Step	Description
1. Define the Study Area	Determine the geographical extent of the study area and the units of analysis.
2. Construct a Spatial Weights Matrix	Create a matrix defining spatial relationships between units, specifying neighbor relationships and weights.
3. Calculate Spatial Autocorrelation	Compute a measure of spatial autocorrelation for the variable across the study area (e.g., Moran's I).
4. Calculate LISA	For each unit, calculate a local Moran's I statistic to measure local spatial association.
5. Assess Significance	Test the significance of local Moran's I value to identify significant clusters or outliers.
6. Visualize Results	Map the results of the LISA analysis to visualize significant

	spatial patterns across the study area.

Three new variables were created in GeoDa based on the same energy poverty indicators determined in RQ1. The median energy expenditure of these variables by each Appalachian state was calculated and is explored in Table A3.

Once the data for each energy poverty indicator relevant to each state was put into GeoDa it is essential to ensure the attributed data is correctly formatted and free of errors. Also, to understand the spatial distribution and check data quality is done through visualization tools. This preliminary step is fundamental to ensure the robustness and reliability of the subsequent analysis. From here a spatial weights matrix is created. The spatial weights matrix (Table A4) defines the spatial relationships between the units of analysis. The matrices used are based on contiguity (e.g., a queen's contiguity matrix). The matrix can be calculated in GeoDa or by hand (Table A4 and A5).

Spatial autocorrelation statistics consists of using varied measures of attributes to assess similarity between two observations, $f\left(x_i, x_j\right)$, using spatial weights, W_{ij}, for indicators with aligned for geography and locality. The generic representation for a local indicator for assessing spatial associations is:

$$\sum_j W_{ij}\, f\left(x_i, x_j\right)$$

Anselin (1995) posits the Local Moran statistic to identify local clusters and local spatial outliers. Row-standardized weights are used and so, the sum of all weights $S_0 = \sum_i \sum_j w_{ij}$ is equal to the number of observations, n. Resulting from this, the Moran's I statistic simplifies to:

$$I = \frac{\sum_j W_{ij}\ Z_i Z_j}{\sum_i Z_i^2}$$

However, assessing significance alone is not that useful for the Local Moran, but combining it with the location on the Moran Scatterplot makes for a more valid and robust interpretation. Table 5 outlines an approach where the classification for significant locations spatial clusters as High-High and Low-Low, is paired with High-Low and Low-High spatial outliers. The data for high and low is relative to the mean variable, and this is important for interpretation.

Table 3: Summary of the concepts used to identify Hot Spots, Cold Spots, and Spatial Outliers for GeoDa analysis.

Category	**Description**
Hot Spots	Identify significant high-high clusters where high values of the energy poverty measure cluster together.
Cold Spots	Identify significant low-low clusters where low values of the energy poverty measure cluster together.
Spatial Outliers	Detect spatial outliers, including high-low (high value surrounded by low values) and low-high (low value surrounded by high values) clusters.

Through this process, the significance of the local Moran's I values was assessed using a permutation approach involving randomization tests to generate a distribution of Moran's I under the null hypothesis of spatial randomness. The 999 permutation was used. Cluster maps present significance but with the significant locations color coded by type of spatial autocorrelation. To obtain more robust results, it is good practice to increase the number of permutations to 999 (Anselin, 2005)

The results from GeoDa were then presented as cluster maps to visualize the results. These maps demonstrate the spatial clusters of similar values and their significance levels. It highlights areas with significant spatial autocorrelation and identifies whether they are high-high, low-low, high-low, or low-high clusters. Therefore, a cluster map for each energy poverty indicator was created to visualize significant hot spots, cold spots, and outliers. The results were interpreted focusing on the spatial patterns and further analysis of the implications of the identified clusters in the context of energy poverty are presented in the discussion. This methodological approach in GeoDa ensures a systematic and rigorous analysis of spatial data, providing valuable insights into spatial associations and distributions to answer the research question.

3.3 Methods to Identify traits associated with different Energy Poverty Indicators

By taking into consideration the descriptive statistics from the RECS dataset, variables were selected to create two models to assess where there might be hot and cold spots in the Appalachian region dependent upon which indicator of energy poverty is utilized. To maintain data integrity and reduce biases that could arise from incomplete data, the data was assessed for missing data by excluding records with significant missing information. Basic descriptive statistics were calculated, including mean, median, variance, and standard deviation for key variables, to summarize the data and provide an overview of energy consumption patterns.

The three indicators of energy poverty were used as dependent variables. For each indicator, two models are estimated for each indicator. Model 1 acts as the base model and Model 2 helps in capturing more comprehensive information by including additional variables, thereby providing deeper insights and more reliable results. Table A6 notes the variables selected for models 1 and 2. The second model looked to capture the effect of energy poverty on one's life, such as home comfort (e.g., HomeTempWINTER, HomeTempSUMMER, Drafty, Adequate Insulation) and including if they have ever received any form of energy assistance (ENERGYASSTOTH) through the addition of 5 variables (See Table 7, 8 and 9). Logit regression was used to explore factors that make being in energy poverty more likely. Once completed, a Variance Inflation Factor was utilized to identify multicollinearity in the multiple regression analyses.

The assessment of spatial distribution per energy poverty indicator was undertaken based on the logit results. Focusing primarily on the results of the coefficient, with the p-value was used to determine the level of significance with the log odds providing more detailed information as to the "odds of being in energy poverty". The 13 states within the Appalachian region and the likelihood of the state playing a factor in being a hot or cold spot for energy poverty were visualized in maps.

4. Results

The current section reports the results of the literature review (4.1) followed by the spatial analysis (4.2) and ending with the statistical analysis (4.3).

4.1 Energy Poverty Indicators

Due to the complex multi-faceted character of energy poverty, some indicators are more sensitive to specific energy poverty drivers than others (Siksnelyte-Butkiene et al., 2022; Mulder et al., 2023). Therefore, it is vital to assess energy poverty by different indicators to include all households affected by this problem (Mulder et al., 2023).

4.1.1 Overview of Energy Poverty Indicators

Assessing the literature for energy poverty indicators reveals diverse methodologies, scopes, and implications for policy and research. Indicators of energy poverty can be divided into single indicators and composite indicators. Single indicators focus on specific aspects of energy access or consumption which provide a straightforward assessment but may lack comprehensive insights. Composite indicators combine various indicators into a single index, offering a more holistic view of energy poverty but can be complex to interpret.

The single energy poverty indicators resulting from the Literature Review in Section 3.1 are found in Table 4 alongside a description. While some of the indicators, such as the >10% indicator and the MIS, primarily focus on financial thresholds to identify energy poverty, others, like the European Union Statistics on Income and Living Conditions (EU-SILC), incorporate subjective measures like inability to keep homes adequately warm or cool (Boardman, 1991; Moore, 2012; Alkire et al., 2014). In contrast, indicators like the After-Fuel-Cost Poverty (AFCP) and the Low Income High Cost (LIHC) emphasize the interaction between energy expenditure and income levels, targeting households facing financial strain due to energy expenses (Hills, 2011; Bouzarovski & Petrova, 2015). Despite these differences, all indicators aim to capture the multifaceted nature of energy poverty, albeit through different lenses, facilitating tailored policy interventions and promoting a comprehensive approach to addressing energy poverty.

Table 4: A summary of single indicators of energy poverty (EP) from the literature, along with their descriptions and sources

Indicator	Description of EP Indicator	Sources
10%	Classifies a household as energy-poor if 10 percent or more income is spent on energy services	Boardman (1991); Siksnelyte-Butkiene et al. (2022)
Twice the National Median	A household is considered to be in EP if it spends more than twice the median share of its income on energy costs	Castano-Rosa, Sherriff, Thomson, Guzman, & Marrero (2019)
Minimum Income Standard (MIS)	A household is identified as being in energy poverty if its income, after accounting for energy services expenditure, falls below the minimum income standard.	Moore (2012)
Low Income High Cost (LIHC)	Classifies a household based on the status of EP, when a household's income after energy services expenditure falls below the official poverty threshold	Hills (2012)

After-Fuel-Cost Poverty (AFCP)	Considers EP if remaining income, after covering housing and other basic needs, is insufficient to pay for essential energy services	Hills (2011)
EU-SILC	Inability to keep the home adequately warm or cool; the house has a leaking roof, damp walls/floors/foundations, rot in window frames; Arrears on utility bills	Alkire et al. (2014); Alkire et al. (2013)

Beyond single indicators of energy poverty, composite indicators have been developed to address energy poverty, described in Table 5. The composite indicators vary in their methodologies, scope and applications. One notable composite indicator is the Multidimensional Energy Poverty Index (MEPI), which integrates diverse dimensions of energy poverty, including income, energy expenditure, and housing conditions (Nussbaumer et al., 2017). Similarly, the Energy Poverty Index (EPI) adopts a holistic approach by combining various indicators related to energy access, affordability, and quality (Sovacool & Dworkin, 2015). Both MEPI and EPI strive to capture the multifaceted nature of energy poverty, emphasizing the importance of considering not only income but also other socio-economic factors.

In contrast, the Energy Vulnerability Index (EVI) focuses specifically on assessing the vulnerability of households to energy poverty (Bouzarovski & Petrova, 2015). Unlike MEPI and EPI, which provide broad assessments of energy poverty, EVI offers a targeted analysis aimed at identifying households at higher risk of energy deprivation. Another distinct composite indicator is the Household Energy Insecurity Access Scale (HEIAS), which evaluates the adequacy, reliability, and affordability of household energy supply. HEIAS includes traditional indicators of energy poverty and additionally tries to encompass the coping strategies employed by households to manage energy-related challenges (Sovacool et al., 2017). This emphasis on coping strategies provides insights into the adaptive capacities of households in dealing with energy insecurity, offering a unique perspective on energy poverty assessment. Furthermore, the Sustainable Energy for All (SE4ALL) Index assesses progress towards achieving universal energy access, encompassing aspects of energy poverty such as energy access, efficiency, and renewable energy adoption (Bhatia and Angelou, 2014). Unlike other composite indicators that focus primarily on assessing the extent of energy poverty, SE4ALL evaluates the effectiveness of policy interventions and initiatives aimed at addressing energy poverty on a global scale.

Table 5: Outline of selected composite indicators of energy poverty, providing descriptions of each and key sources for reference.

Indicator	Description	Key Sources
Multidimensional Energy Poverty Index (MEPI)	Integrates multiple dimensions of energy poverty, such as income, energy expenditure, and housing conditions, to provide a comprehensive indicator of energy poverty status	Nussbaumer et al. (2017); Alkire et al. (2013)
Energy Poverty Index (EPI)	Combines various indicators related to energy access, affordability, and quality to assess the overall energy poverty level in each area	Sovacool & Dworkin (2015); Bouzarovski & Petrova (2015)
Energy Vulnerability Index (EVI)	Evaluates the vulnerability of households to energy poverty by considering factors such as income level, energy expenditure, housing quality, and access to energy services	Bouzarovski & Petrova (2015); Heindl & Schuessler (2017)
Household Energy Insecurity Access Scale (HEIAS)	Assesses the adequacy, reliability, and affordability of household energy supply, along with the coping strategies employed by households to manage energy-related challenges	Sovacool et al. (2015); Carley et al. (2017)
Sustainable Energy for All (SE4ALL) Index	Indicators progress towards achieving universal energy access, including aspects of energy poverty such as energy access, energy efficiency, and renewable energy adoption	Bhatia & Angelou (2014); Lucon et al. (2014)

Critiques of composite indicators for energy poverty in the US highlight several key concerns. Methodological complexities, such as the subjective selection and aggregation of indicators, raise questions about the validity and comparability of results (Sovacool & Dworkin, 2015). Additionally, reliance on aggregate data sources may obscure localized variations in energy poverty experiences, hindering the identification of specific needs within communities or demographic groups (Bouzarovski & Petrova, 2015). Concerns also extend to the policy relevance of composite indicators, with doubts about their effectiveness in guiding targeted interventions due to their complexity and potential lack of clarity for policymakers (Bouzarovski, 2014). The challenge of balancing simplicity and comprehensiveness in indicator design underscores the need for careful consideration of trade-offs to ensure that composite indicators effectively inform policy responses to energy poverty in the U.S. context (Alkire et al., 2013).

4.1.2 Selected Energy Poverty Indicators

Three different indicators of energy poverty will be considered in this thesis to attempt to include the multifaceted nature of energy poverty. The three indicators will be:

Indicator 1: (>10%) Does the household (owner) spend more than ten percent of its income on all energy used in the home?

Indicator 2: (Mx2) Does the household (owner) spend more than twice the median proportion of income to others in their state?

Indicator 3: (HEP) Does the household (owner) reduce or forgo necessities due to home energy bills and so potentially experience *hidden energy poverty*?

The choice is substantiated by Boardman's seminal work (1991), which proposed the 10% indicator threshold, widely recognized within scholarly discourse. This criterion offers a practical metric, reflecting the strain of energy expenses on household budgets. The Mx2 indicator represents the proportion of households whose share of energy expenditure in income is more than twice the national median share Additionally, the Mx2 indicators aligns with insights from the Hills Report (2012), emphasizing a clear distinction between income deciles and captures households with abnormally high energy expenditure relative to income. Moreover, both indicators rely on readily available income and expenditure data, facilitating their implementation at scale, as outlined in the Hills Report (2012). This pragmatic approach enables policymakers to efficiently target energy-poor households for intervention programs or policy initiatives.

Including indicators of HEP in assessing overall energy poverty is crucial as it captures households severely deprived of adequate energy services that traditional expenditure-based metrics may miss (Kos Grabar Robina et al., 2022; Eisfeld and Seebauer, 2022; Cong et al., 2022). HEP in the literature refers to households underutilizing energy due to affordability constraints, poor housing conditions, or self-rationing energy use (Eisfeld and Seebauer, 2022; Cong et al., 2022). The variable from the RECS survey chosen to assess potential HEP was SCALEB which asks respondents the “Frequency of reducing or forgoing basic necessities due to home energy bill.” Incorporating HEP provides a comprehensive understanding of energy deprivation, aiding in creating a more holistic picture of populations experiencing energy poverty (Eisfeld and Seebauer, 2022). Identifying HEP can target assistance to households using risky coping strategies like unsafe heating or forgoing essential energy services (Cong et al., 2022;). Accounting for HEP is vital to avoid underestimating its prevalence, capture its multidimensional nature, and design effective policies to alleviate all forms of energy poverty, including less visible forms. Thus, the employment of >10%, Mx2, and HEP indicators are robust ways to evaluate energy poverty in the U.S. and feasible with existing data.

4.2 Results of Spatial Distribution of the Energy Poverty Indicators

To investigate the spatial distribution of energy poverty indicators, the analysis centered on homeowners across the 13 states comprising the Appalachian region, Figure 1. The analysis of the region is shown in Figure 2. While the Appalachian region is defined by county level, the RECS dataset provides state level data, so the 13 states will be considered.

Table 4 developed income deciles inclusive of both renters and owners, and the proportion of households in each decile considered low income by the LIHEAP definition (see Section 2). Further on, only owners will be considered in the analysis to avoid the "split incentive problem." This refers to a situation in which the party responsible for making an investment to improve energy efficiency (e.g., upgrading insulation or installing energy-efficient appliances) is not the same party who benefits from the resulting energy cost savings. This misalignment of incentives can create barriers to energy efficiency improvements in residential or commercial buildings. Scholars like Laquatra (1987) and Bird and Hernández (2012) have discussed various aspects of the split incentive problem and explored potential solutions, such as policy interventions, financial incentives, or innovative contracting arrangements, to align the interests of building owners, tenants, and other stakeholders towards energy efficiency improvements.

Table 4: Income deciles and disproportionate energy expenditure by ownership status and income decile. This table only includes low-income respondents.

Income Decile	D1	D2	D3	D4	D5	D6	D7	D8
Average Income	$2,500.00	$6,249.50	$8,749.50	$11,249.50	$13,749.50	$17,499.50	$22,499.50	$27,499.50
Owners								
Energy Cost > 10%	99.44%	93.24%	87.36%	83.08%	54.45%	45.45%	23.76%	12.18%
Energy Cost > Mx2	5.06%	2.70%	3.45%	3.59%	1.05%	1.62%	3.76%	3.57%
HEP	40.45%	47.30%	43.68%	41.03%	34.55%	26.95%	27.13%	24.58%
Renters								
Energy Cost > 10%	99.15%	87.32%	62.35%	46.15%	30.63%	18.55%	11.59%	5.52%

Energy Cost > Mx2	2.56%	0.70%	1.23%	0.45%	1.25%	1.21%	0.91%	1.38%
HEP	47.01%	45.77%	43.21%	43.44%	40.63%	39.11%	42.38%	38.62%

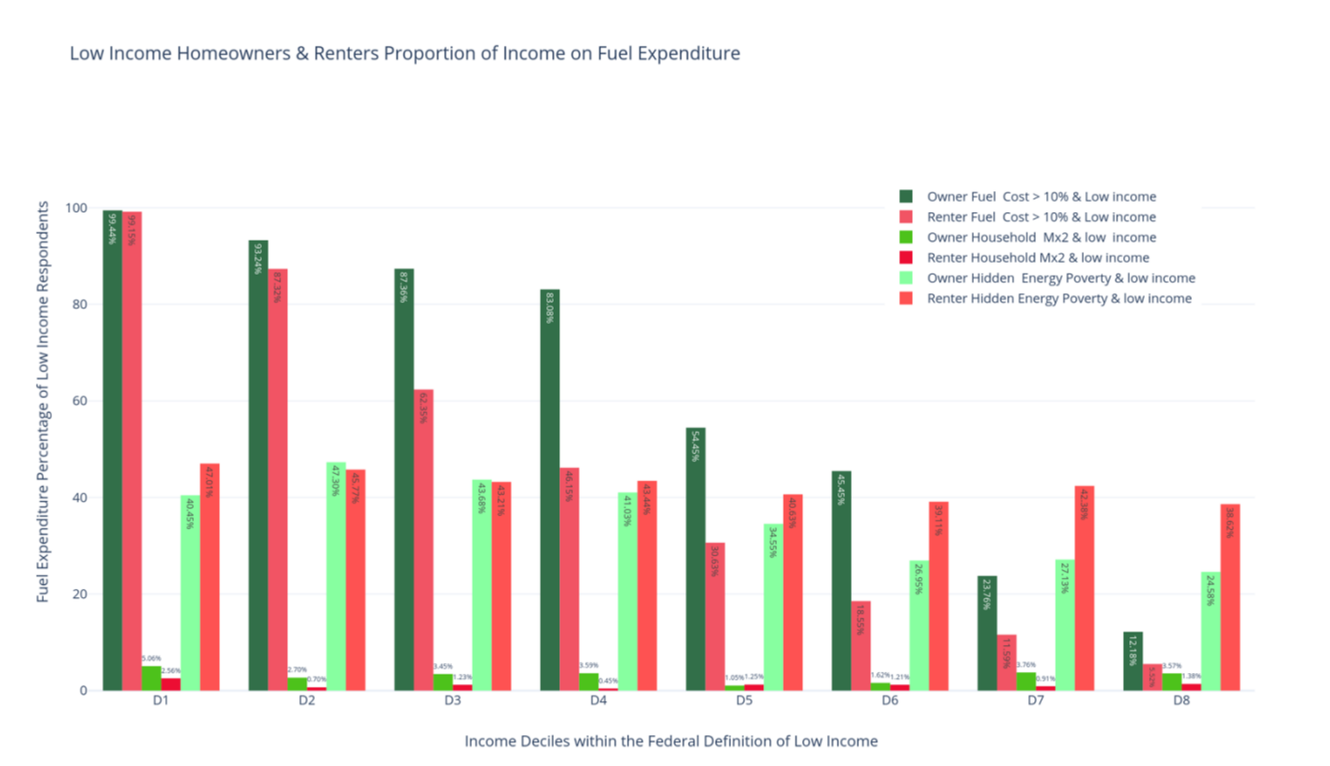
The indicator of energy costs exceeding 10% of income shows the highest prevalence among lower-income groups (see Figure 2 below, and Table A2). Notably, nearly all homeowners in these lower income categories experience energy costs surpassing 10% of their income. For instance, within the income group D1 total homeowners, 99.44% are affected. Conversely, the percentage of homeowners with high energy costs diminishes markedly in higher income groups, eventually reaching 0% in the highest income categories. For both homeowners and renters, the indicator of energy costs exceeding 10% of income shows the highest prevalence among lower-income groups. Among homeowners, nearly all in the lowest income categories experience high energy costs, with figures such as 99.44% in a group of 178. For renters, this pattern is similar, but the exact percentages may vary due to differences in housing costs and energy efficiency of rental properties.

The incidence of households spending more than twice the median proportion of their income on energy (Mx2) is generally low across all income groups. In low-income groups, this indicator ranges from 1.05% to 5.06%. For higher income groups, the percentage is consistently 0%, indicating that this issue predominantly affects lower-income households, hence the focus of the low-income deciles 1-8. The incidence of households spending more than twice the median proportion of their income on energy remains low across all income groups for both owners and renters. In lower-income groups, the indicator ranges from 1.05% to 5.06% for owners and likely follows a similar pattern for renters, though renters might experience slightly higher variability due to differing lease terms and energy inclusions.

Hidden energy poverty, which represents households that are energy-poor but not visibly so, shows significant prevalence in lower-income groups. In a lower income group (D2) for homeowners, the percentage reaches a peak of 47.30%. As income increases, the percentage of households experiencing HEP drops substantially, falling to 2.30% in the highest income group. This trend underscores the pronounced impact of HEP on lower-income households. Hidden energy poverty, representing households that are energy-poor but not visibly so, is significantly prevalent among lower-income groups for both owners and renters. Renters in the lowest income groups surpass owners, showing a peak of 47.10%, and exceeding owners in deciles D1 and D4 -

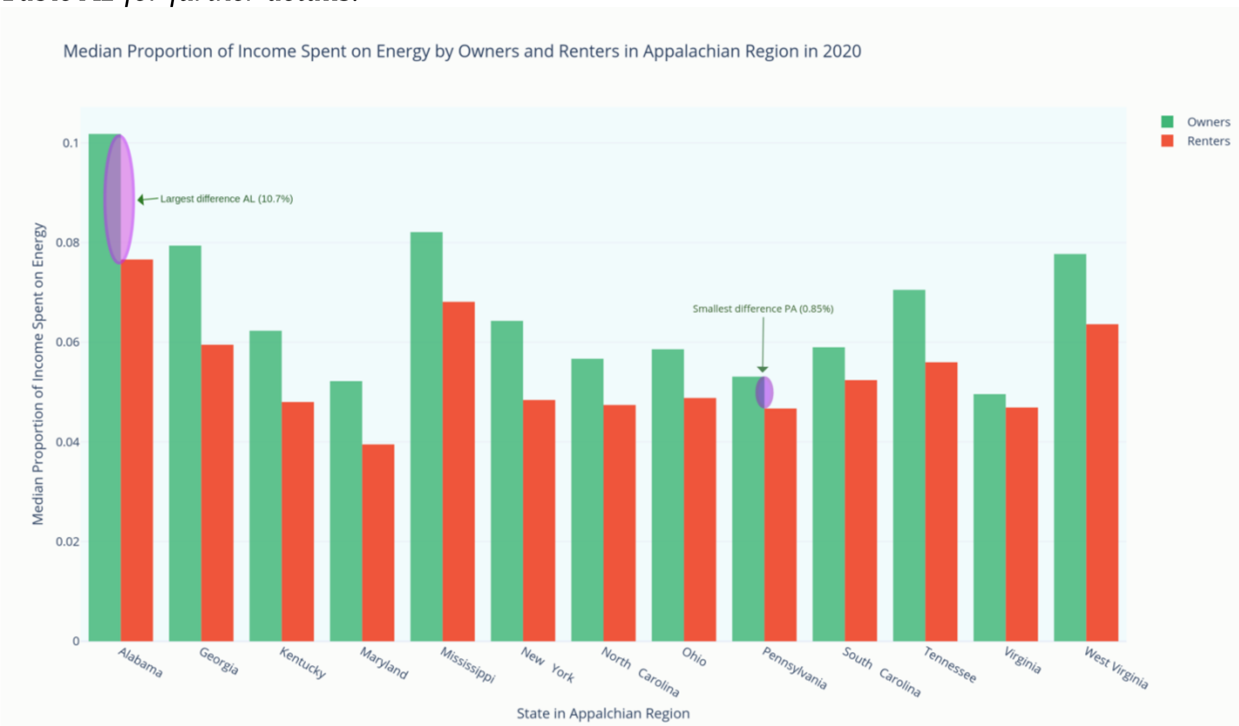
D8. Renters show higher percentages as they often face higher utility costs relative to their income. As income increases, the percentage of households experiencing HEP drops substantially for both owners and renters, reaching as low as 2.30% in the highest income group for homeowners and similarly low levels for renters.

Figure 2: Proportion of income spent on energy expenditure for exclusively low-income respondents (income deciles 1-8) in the RECS survey. Both homeowners (green) and renters (red) are included with each being compared via the 3 indicators of energy poverty.



There are discernable patterns in the median proportion of income allocated to energy expenses within households, particularly concerning tenure status and regional disparities in energy pricing. Across various states, owners and renters exhibit varying allocations of their income towards energy expenditure, see Figure 3. Notably, renters generally allocate a higher proportion of their income to energy compared to homeowners. The proportion of income devoted to energy expenses is noteworthy in states such as Alabama and Mississippi indicating a substantial burden on renters, with median proportions of income spent on energy reaching 18.36% and 13.49%, respectively. Conversely, states like Maryland and Virginia suggest relatively lower burdens on renters, with proportions of 8.12% and 5.75%, respectively. A comparative examination between owners and renters underscores considerable disparities, particularly in states like Alabama and Mississippi, where the gap in median proportions of income allocated to energy expenses between these two groups is most pronounced, at 10.7% and 6.68%, respectively. Conversely, states like Pennsylvania and Virginia exhibit a narrower gap, indicating a more equitable distribution of energy costs between owners and renters, with differences of 0.85% and 1.06%, respectively.

Figure 3: Median proportion of income spent on energy in 2020 by both renters and owners. See Table A1 for further details.



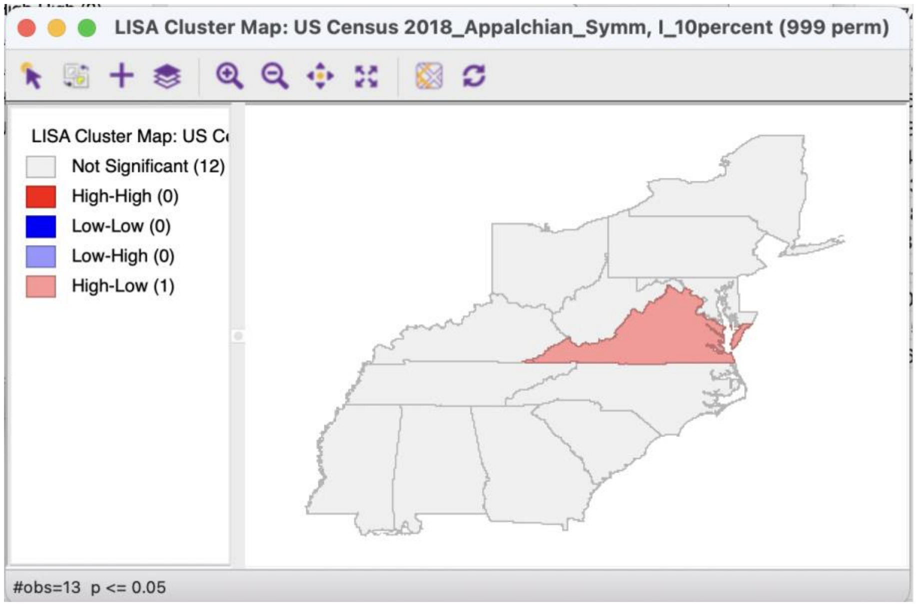
It is worthwhile to consider what role electricity prices contribute to energy poverty. New York exhibits significantly higher utility rates, which likely exacerbate the energy cost burden, particularly for renters. In contrast, states such as Virginia and West Virginia benefit from lower electricity prices, potentially mitigating the financial pressure of energy expenses. Likewise, disparities in natural gas prices further highlight these regional differences; New York's elevated rates correspond to a higher energy cost burden, whereas states like Kentucky and Ohio benefit from lower natural gas prices, potentially reducing the proportion of income devoted to energy expenses.

Figure 3 reveals several key insights regarding the energy cost burden experienced by households, particularly in the context of rental versus ownership status and regional variations in energy prices. Renters generally bear a higher energy cost burden compared to homeowners, a trend attributed to potentially lower income levels among renters and the variability in energy prices across states. Regional disparities in energy prices are notable, with states in the Northeast, such as New York, exhibiting higher energy prices relative to those in the South and Midwest. These findings underscore the importance of targeted energy assistance programs, particularly in states like Alabama and Mississippi where the disparity in energy cost burden between renters and owners is most pronounced. Additionally, the analysis emphasizes the necessity of considering both electricity and natural gas prices, as well as the proportion of income allocated to energy expenses, to gain a comprehensive understanding of the overall energy cost burden on households. Such insights are crucial for informing policy interventions aimed at addressing energy affordability and promoting equitable access to essential energy services.

To further elucidate these spatial disparities, spatial analysis was employed. The Local Indicators of Spatial Association (LISA) in GeoDa helps to identify and visualize clusters of spatial data. The energy expenditure for the 3 indicators of energy poverty for household owners in the 13 Appalachian states informed the analysis.

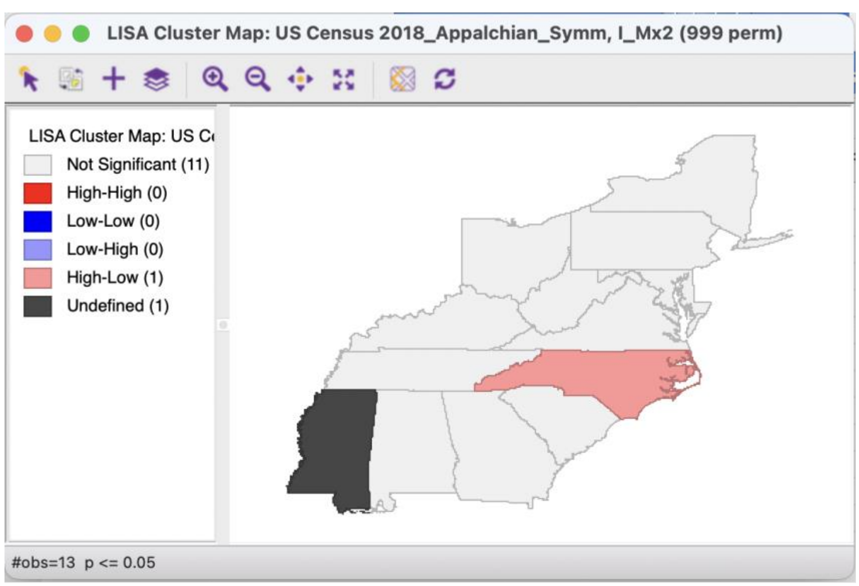
The LISA analysis of Indicator 1: >10% identified Virginia as High-Low meaning it is a state whose energy expenditure as measured by >10% is a high value distinctly different from the low values of their surrounding neighbors (See Figure 4). A high-low result is a negative local spatial autocorrelation (Anselin, 2005) and labeled as a spatial outlier.

Figure 4: GeoDa LISA cluster map of Indicator 1: >10% of energy expenditure of low-income homeowners.



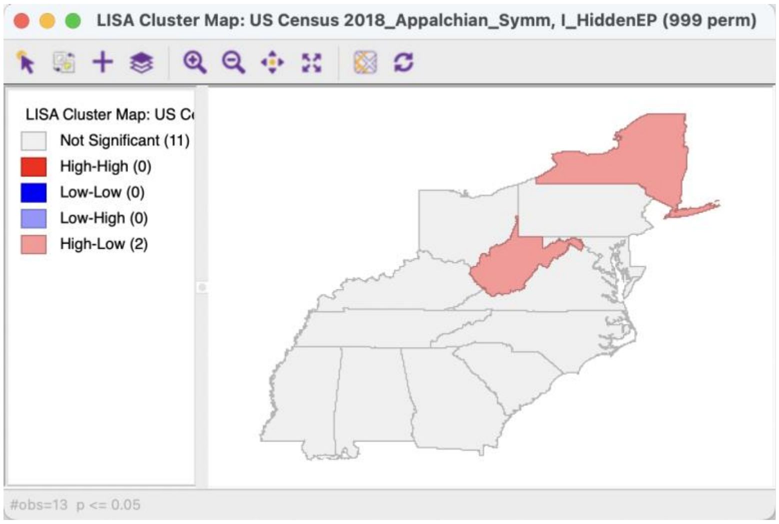
Under Indicator 2: Mx2 North Carolina is identified as High-Low (see Figure 5). Therefore North Carolina's energy expenditure, as measured by Mx2, is a spatial outlier. Therefore North Carolina's high value is distinctly different from the low values of their surrounding neighbors. Mississippi has no responses that met this criterion which is represented as black.

Figure 5: GeoDa LISA cluster map of Indicator 2: Mx2 of energy expenditure of low-income homeowners.



Finally, the LISA of Indicator 3: HEP identifies two states as High-Low, noting New York and West Virginia's HEP as areas with high values surrounded by areas with low values (see Figure 6). These indicate statistical significance compared to their neighbors.

Figure 6: GeoDa LISA cluster map of Indicator 3: Hidden Energy Poverty energy expenditure of low-income homeowners.



The LISA analysis reveals minimal spatial clustering of median energy expenditures among low-income homeowners in most states, particularly Mississippi, Ohio, Maryland, North Carolina, Alabama, Tennessee, and New York. Overall, the findings highlight the importance of considering spatial factors alongside non-spatial factors in addressing energy poverty and suggest that policy interventions should be tailored to the specific socioeconomic contexts of each state. Building on these insights, further statistical analysis was conducted to identify additional descriptors of energy poverty using the RECS 2020 dataset.

4.3 Results of Statistical Descriptors of Indicators on Homeowners in Appalachia

Considering the findings of the spatial analysis of the Appalachian region of the U.S. using the RECS 2020 dataset, further statistical analysis was done to potentially identify additional descriptors of energy poverty. To analyze the three indicators of energy poverty identified (e.g., >10%, Mx2, HEP), two logit models are used to explore variables associated with energy poverty.

The results are summarized in Table 5 and presented in Tables 6, 7, and 8, with significance noted by asterisks[3].

Table 5: Summary of results from the 3 indicators of energy poverty and the 2 models.

Energy Poverty Indicator	(Model 1) Significant Predictors	(Model 2) Significant Predictors
Energy Cost > 10%	AirCond, Numofmem, EduHS	AirCond, Numofmem, EduHS
Energy Costs > Mx2	AirCond, Numofmem, EduHS	AirCond, Numofmem, EduHS
Hidden Energy Poverty	AirCond, ENERGYASST, Numofmem	AirCond, Numofmem, EduHS

4.3.1 Indicator 1: Energy Costs greater than 10%

In this section the results from two models of logit regressions are interpreted for each of the three energy poverty indicators to assess if any household traits are associated with the energy poverty indicators in Appalachia. In Table 6, Model 1, air conditioning usage (AirCond) significantly decreases the likelihood of being in energy poverty by almost 60% (1 - 0.391). However, In Model 2, air conditioning is now associated with higher odds of energy costs exceeding 10%. The data from Model 1 and 2 suggests that families living in a single-family home (SingleFamily) have lower odds of high energy costs, reducing the odds by about 47% (1 - 0.528) and 46.4% (1 - 0.536) respectively. Both models indicate that an increase in the number of household members (Numofmem) is associated with a decrease in the odds of experiencing energy costs greater than 10%. The relationship is consistent across both models, with Model 2 showing a slightly stronger effect and higher statistical significance.

Both models indicate a female headed household is less likely to experience energy costs greater than 10%. The odds of having energy costs greater than 10% are 48.1% lower (Model 1 at 1 - 0.519) for female-headed households compared to male-headed households, and in Model 2 the odds are 43.8% lower (1 - 0.562). The relationship is consistent and highly significant across both models. However, the magnitude of the effect is slightly smaller in Model 2, which includes

[3] * A single asterisk indicates a p-value less than or equal to 0.05 ($p \leq 0.05$).
** Two asterisks indicate a p-value less than or equal to 0.01 ($p \leq 0.01$).
*** Three asterisks indicate a p-value less than or equal to 0.001 ($p \leq 0.001$).
**** Four asterisks indicate a p-value less than or equal to 0.0001 ($p \leq 0.0001$).

additional variables, suggesting that these additional factors might slightly mediate the effect of gender on energy poverty.

Another trait of note is if the respondent has full-time employment status (Employ FullTime) they are more likely to experience energy costs greater than 10%, with Model 2 (LogOdds = 2.124) being slightly smaller than in Model 1 (LogOdds = 2.168). The relationship is consistent and highly significant across both models, with a slight reduction in the magnitude of the effect in Model 2.

Finally, there is a strong relationship between education level and the likelihood of experiencing high energy costs. Households with lower education levels (e.g., Edu No HS, Edu HS, EduSomeUni) face significantly higher odds of having energy costs greater than 10%, with the effect being most pronounced for those without a high school diploma. The inclusion of additional variables in Model 2 slightly reduces the observed effects, but the relationship remains significant.

Table 6: Logit regressions of Appalachian homeowners in energy poverty for Indicator 1: spending >10% of income on energy.

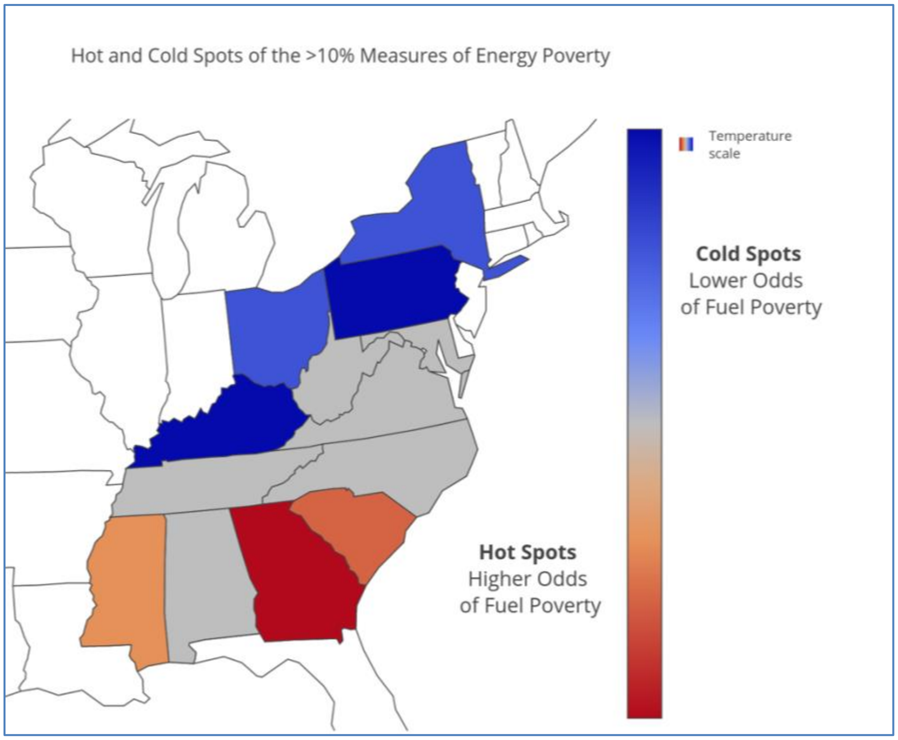
Indicator 1: Energy Costs > 10%

	Model 1		Model 2	
Variable	**Coeff. (S.E.)**	**Log Odds**	**Coeff. (S.E.)**	**Log Odds**
TotalDOL	0**** (0.000)	1	0**** (0)	1
AirCond	-0.939**** (0.218)	0.391	0.495 (1.182)	1.64
SingleFamily	-0.639**** (0.153)	0.528	-0.623**** (0.151)	0.536
HomeAge	-0.146**** (0.034)	0.864	-0.113** (0.036)	0.893
Numofmem	-0.152* (0.066)	0.859	-0.181** (0.068)	0.834
TotalArea Sq.ft.	0**** (0.000)	1	0**** (0)	1
HDD65	0 (0.000)	1	0 (0)	1
CDD65	0 (0.000)	1	0 (0)	1
Gender	-0.655**** (0.147)	0.519	-0.576**** (0.15)	0.562
Race	0.216** (0.072)	1.241	0.196* (0.076)	1.216
Age	-0.008 (0.007)	0.992	-0.007 (0.007)	0.993
Over65	-0.255* (0.121)	0.775	-0.199 (0.123)	0.819
AtHome	0.077 (0.060)	1.08	0.113 (0.062)	1.12
Edu No HS	2.986**** (0.403)	19.806	2.777**** (0.408)	16.066
Edu HS	2.474**** (0.358)	11.867	2.406**** (0.36)	11.093
EduSomeUni	1.563**** (0.362)	4.773	1.439**** (0.366)	4.217
EduBA	0.519 (0.402)	1.68	0.47 (0.404)	1.6

Employ FullTime	0.774**** (0.076)	2.168	0.753**** (0.077)	2.124
Urban	-0.226 (0.240)	0.798	-0.229 (0.248)	0.796
Rural	0.264 (0.231)	1.302	0.28 (0.24)	1.322
AL	0.637 (0.467)	1.89	0.594 (0.481)	1.812
GA	0.912 (0.462)	2.49	0.81 (0.476)	2.248
KY	-0.133 (0.370)	0.875	-0.096 (0.383)	0.909
MD	0.034 (0.452)	1.034	0.106 (0.462)	1.112
MS	0.912 (0.505)	2.49	0.911 (0.521)	2.488
NY	-0.565 (0.403)	0.568	-0.418 (0.415)	0.658
NC	0.163 (0.435)	1.176	0.096 (0.448)	1.101
OH	-0.322 (0.399)	0.725	-0.225 (0.41)	0.798
PA	-0.255 (0.364)	0.775	-0.173 (0.376)	0.841
SC	0.734 (0.460)	2.084	0.785 (0.473)	2.193
TN	0.311 (0.374)	1.365	0.333 (0.387)	1.396
VA	0.108 (0.390)	1.114	0.146 (0.404)	1.157
HomeTemp WINTER			-0.011 (0.011)	0.989
HomeTemp SUMMER			-0.02 (0.016)	0.981
DRAFTY			-0.055 (0.11)	0.947
ADQINSUL			0.271* (0.114)	1.311
ENERGYASST			0.648**** (0.106)	1.912
Constant	-3.988* (1.668)	0.019	-1.758 (1.897)	0.172

The two models reveal significant disparities between using the >10% energy poverty across the Appalachian region. States such as Georgia, Mississippi, and South Carolina are identified as “hot spots” as they exhibit markedly higher odds of households facing energy costs exceeding 10%, pointing to a prevalence of energy poverty in these regions. Conversely, states like Kentucky, New York, Ohio, and Pennsylvania are identified as “cold spots” as they display lower odds, indicating a lesser prevalence of this issue. States such as Maryland and Virginia show coefficients approaching zero, suggesting minimal to no significant impact on the likelihood of experiencing high energy costs. These results are visualized in Figure 7.

Figure 7: The states identified as hot and cold spots of Indicator 1: Greater than 10% indicator of energy poverty.



4.3.2 Indicator 2: Energy Costs greater than Mx2

In analyzing the determinants of spending more than twice the median income on energy, significant predictors emerged across two models. In Model 1, Table 7, educational attainment played a crucial role; households without a high school education (Edu No HS) had significantly higher odds (4.482) of excessive energy spending, followed closely by those with only a high school diploma (Edu HS) (Log Odds: 3.615). Model 2, table 7, reaffirmed the influence of educational attainment, with households holding a high school diploma exhibiting an extraordinary increase in the odds (Log Odds: 772.57) of excessive energy expenditure.

Household size also positively influenced energy expenditure, with each additional member increasing the odds by 30.7%. Conversely, households with members over 65 years old had a 30% lower likelihood of high energy spending. Additionally, energy assistance emerged from Model 2 as a significant factor, nearly tripling the odds (2.857) of high energy spending among respondents who identified as assistance recipients.

Table 7: Logit regressions of Appalachian homeowners in energy poverty for Indicator 2: spending more than the median times 2 of income on energy.

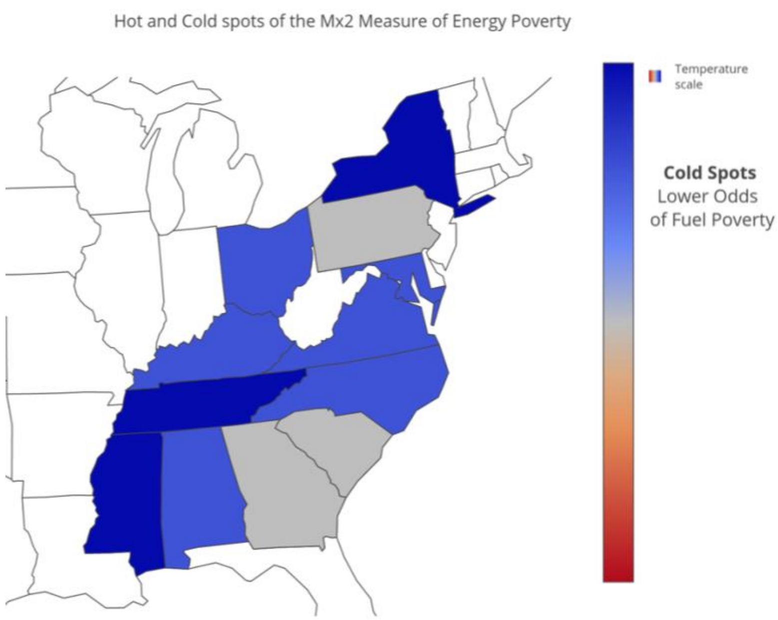
Indicator 2: Energy Costs > Median x 2

	Model 1		Model 2	
Variable	**Coeff. (S.E.)**	**Log Odds**	**Coeff. (S.E.)**	**Log Odds**
TotalDOL	0**** (0)	1	0.001 (0)****	1.001
AirCond	-0.561** (0.183)	0.571	5.88 (3.505)	357.766
SingleFamily	-0.193* (0.092)	0.825	-0.786 (0.566)	0.456
HomeAge	-0.073** (0.024)	0.929	-0.408 (0.137)**	0.665
Numofmem	0.268**** (0.042)	1.307	0.271 (0.192)	1.311
TotalArea Sq.ft.	0**** (0)	1	0 (0)	1
HDD65	0* (0)	1	0 (0.001)	1
CDD65	-0.001* (0)	0.999	0 (0.001)	1
Gender	-0.219* (0.102)	0.803	0.919 (0.479)	2.507
Race	0.249**** (0.051)	1.282	0.193 (0.266)	1.212
Age	-0.011* (0.005)	0.989	-0.021 (0.021)	0.979
Over65	-0.357**** (0.093)	0.7	0.761 (0.347)*	2.14
AtHome	-0.045 (0.034)	0.956	-0.247 (0.201)	0.781
Edu No HS	1.5**** (0.254)	4.482	4.186 (2.834)	65.792
Edu HS	1.285**** (0.183)	3.615	6.65 (2.646)*	772.57
EduSomeUni	1.092**** (0.175)	2.982	4.989 (2.611)	146.817
EduBA	0.243 (0.189)	1.275	4.498 (2.551)	89.857
Employ FullTime	0.276**** (0.05)	1.317	0.525 (0.251)*	1.691
Urban	-0.088 (0.178)	0.916	-1.114 (1.327)	0.328
Rural	-0.138 (0.182)	0.871	1.726 (1.144)	5.619
AL	-0.378 (0.361)	0.686	0.729 (1.398)	2.074
GA	-0.329 (0.341)	0.72	0.83 (1.557)	2.293
KY	-0.709** (0.273)	0.492	1.105 (1.25)	3.019
MD	-0.712* (0.302)	0.491	1.126 (1.5)	3.082
MS	-0.328 (0.393)	0.72	-16.043 (2717.259)	0
NY	-0.865** (0.29)	0.421	-0.179 (1.374)	0.836
NC	-0.841** (0.327)	0.431	0.561 (1.423)	1.752
OH	-0.638* (0.302)	0.528	0.828 (1.269)	2.289
PA	-0.522 (0.269)	0.593	-1.706 (1.7)	0.182
SC	-0.397 (0.349)	0.672	1.189 (1.503)	3.284
TN	-0.776** (0.288)	0.46	-0.096 (1.498)	0.909
VA	-0.745** (0.289)	0.475	0.995 (1.28)	2.706
HomeTemp WINTER			-0.017 (0.036)	0.983
HomeTemp SUMMER			-0.084 (0.048)	0.919
DRAFTY			0.327 (0.43)	1.387
ADQINSUL			0.008 (0.389)	1.008
ENERGYASST			1.05 (0.264)****	2.857

Constant	1.615 (1.294)	5.028	-11.636 (6.886)	0

The state-level results indicate that households in Kentucky, Maryland, New York, North Carolina, Ohio, Tennessee, and Virginia are less likely to spend more than twice the median income on energy compared to the reference state, with the effects being most pronounced and statistically significant in Model 1. These "cold spots" are presented in Figure 8. This suggests regional variations in energy spending patterns, potentially influenced by state-level policies, energy prices, or climate conditions. Despite variations in other demographic and home-related factors, the state of residence does not significantly influence the likelihood of the outcome in the context of the variables examined. Therefore, geographical location does not appear to be a significant determinant in either model using Indicator 2: Energy Costs greater than Mx2. Overall, these findings underscore the roles of financial status, home characteristics, demographic factors, and assistance programs in determining the likelihood of the outcome.

Figure 8: The states identified as hot spots and cold spots of Indicator2: Mx2 variable to present the likelihood of being in energy poverty by state based on both model 1 and 2.



4.3.3 Indicator 3: Hidden Energy Poverty

Thirdly, the energy poverty indicator of HEP is considered based on respondents of the RECS survey which confirmed they reduced or went without necessities due to home energy bills. Both models highlight the critical role of educational attainment in influencing hidden energy poverty. Households without a high school diploma or with only a high school diploma are significantly more likely to experience hidden energy poverty. In Model 1, households with only a high school diploma have high odds of experiencing HEP (Log Odds: 415.811) as well as those without a high school diploma (Log Odds: 31.619). In Model 2, the odds for households experiencing HEP are less pronounced with a high school diploma (Log Odds: 3.4) and those without a high school diploma (Log Odds: 3.775), respectively.

Table 8: Logit regressions of Appalachian homeowners in energy poverty for Indicator 3: HEP of forgoing necessities to afford energy bills.

Indicator 3: Hidden Energy Poverty

	Model 1		Model 2	
Variable	**Coeff. (S.E.)**	**Log Odds**	**Coeff. (S.E.)**	**Log Odds**
TotalDOL	0.001 (0)****	1.001	0 (0)	1
AirCond	-0.211 (0.745)	0.81	3.107*** (0.903)	22.357
SingleFamily	-0.844 (0.543)	0.43	-0.165 (0.093)	0.848
HomeAge	-0.349 (0.123)**	0.705	-0.027 (0.025)	0.973
Numofmem	0.322 (0.179)	1.38	0.247**** (0.043)	1.281
TotalArea Sq.ft.	0 (0)	1	0**** (0)	1
HDD65	0.001 (0.001)	1.001	0* (0)	1
CDD65	0.001 (0.001)	1.001	-0.001* (0)	0.999
Gender	0.817 (0.455)	2.264	-0.07 (0.106)	0.932
Race	0.133 (0.249)	1.142	0.217**** (0.053)	1.242
Age	-0.03 (0.019)	0.971	-0.009 (0.005)	0.991
Over65	0.721 (0.323)*	2.056	-0.282** (0.096)	0.754
AtHome	-0.267 (0.177)	0.765	-0.041 (0.035)	0.96
Edu No HS	3.454 (2.584)	31.619	1.328**** (0.265)	3.775
Edu HS	6.03 (2.322)**	415.811	1.224**** (0.188)	3.4
EduSomeUni	4.347 (2.302)	77.231	1.003**** (0.179)	2.727
EduBA	3.647 (2.279)	38.375	0.224 (0.192)	1.251
Employ FullTime	0.573 (0.227)*	1.773	0.261**** (0.052)	1.298
Urban	-0.754 (1.238)	0.471	-0.09 (0.186)	0.914
Rural	1.623 (1.089)	5.066	-0.081 (0.188)	0.922
AL	0.559 (1.301)	1.749	-0.405 (0.375)	0.667
GA	0.771 (1.422)	2.162	-0.433 (0.353)	0.648
KY	0.619 (1.122)	1.857	-0.733** (0.284)	0.48
MD	0.355 (1.402)	1.427	-0.791* (0.315)	0.453
MS	-15.677 (2886.526)	0	-0.436 (0.407)	0.647
NY	-0.92 (1.213)	0.399	-0.779*** (0.299)	0.459
NC	0.461 (1.312)	1.586	-0.892*** (0.338)	0.41
OH	-0.222 (1.112)	0.801	-0.531 (0.313)	0.588
PA	-2.123 (1.471)	0.12	-0.528 (0.28)	0.59
SC	0.96 (1.406)	2.611	-0.394 (0.36)	0.675

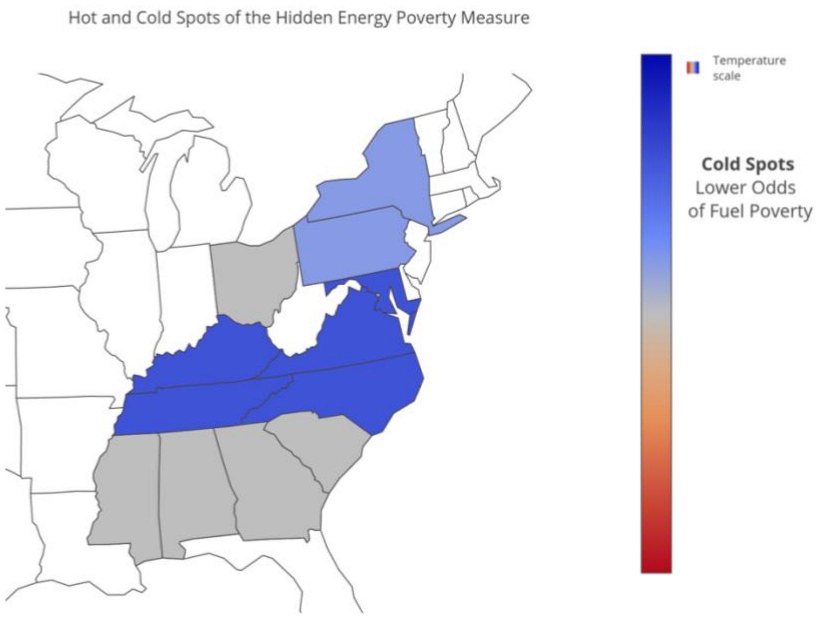
TN	-0.766 (1.5)	0.465	-0.76* (0.298)	0.468
VA	0.587 (1.164)	1.799	-0.789** (0.299)	0.454
HomeTemp WINTER			-0.013 (0.007)	0.987
HomeTemp SUMMER			-0.049**** (0.012)	0.952
DRAFTY			-0.582**** (0.078)	0.559
ADQINSUL			0.085 (0.087)	1.088
ENERGYASST			0.462**** (0.096)	1.588
Constant	-15.639 (6.098)**	0	5.067*** (1.478)	158.713

Model 1 shows that households with members over 65 are more likely to experience HEP (log odds of 2.056). Full-time employment is associated with higher odds of HEP (log odds: 1.773) in Model 1.

Air conditioning in Model 2 is associated with a significantly higher likelihood of HEP (log odds: 22.357). This suggests that the cost of running air conditioning could be a substantial financial burden. In Model 2, larger households have higher odds of HEP (log odds: 1.281), indicating that more members might lead to greater energy consumption and thus higher costs relative to income.

Seen in Figure 9, only cold spots where HEP is less likely to occur resulted from the analysis using Indicator 3. The state variables for Model 1 do not have significance. While the coefficient for NY (-0.92 (S.E.: 1.213)) and PA (-2.123 (S.E.: 1.471)) suggests lower odds of hidden energy poverty, the result is not statistically significant. This indicates that there is no strong evidence to conclude that households in New York or Pennsylvania significantly differ in their likelihood of experiencing HEP compared to the reference. In Model 2, Kentucky (KY), Maryland (MD), North Carolina (NC), Tennessee (TN), and Virginia (VA) exhibit statistically significant reductions in the odds of HEP compared to the reference group. This indicates that households in these states are less likely to experience hidden energy poverty, with the states showing reductions ranging from approximately 52% to 59%. None of the states included in the models exhibit a higher likelihood of HEP compared to the reference group. The coefficients either indicate lower odds or are not statistically significant, suggesting that households in these states are not shown to be at a higher risk of HEP based on the variables included in the models.

Figure 9: The states identified as hot and cold spots of Indicator 3: Hidden Energy Poverty combined from both models 1 and 2.



5. Discussion

The study identified energy poverty indicators to use to spatially assess where energy poverty is more or less likely to occur within the Appalachian region of the U.S. and further examine if certain household traits are associated with any of these implemented energy poverty indicators. Various energy poverty indicators were identified, including single measures like the 10% threshold and Twice the National Median (Mx2), and composite indices such as the Hidden Energy Poverty (HEP). Spatial distribution analysis in the Appalachian region revealed Virginia, North Carolina, New York, and West Virginia as areas of interest for different indicators. Logit regression models identified Georgia, Mississippi, and South Carolina as hotspots by the 10% indicator. The models highlighted household traits influencing energy poverty, with air conditioning availability, number of household members, race, and educational attainment (High School Diploma) showing association with some or all the energy poverty indicators. Cold spots from the household traits were consistently found in Kentucky and New York, while energy poverty was more likely to impact individuals aged 65+ and full-time workers.

The limitations in this study include the range of terminology in this field, limited focus in research on the U.S. context, the simplification of the issue through single indicators alongside the lack of data for composite indicators, as well as the dataset used. The breadth of terminology used within energy poverty literature means potentially relevant literature and therefore indicators may have escaped the search. With the U.S. only recently separating energy poverty from general poverty, less literature is inclusive of the specific geographic context of the US. Single-factor indicators of energy poverty, such as >10% and Mx2, oversimplify the issue by ignoring multiple influencing factors such as income, energy prices, and housing quality. They lack contextual consideration for regional variations in energy costs and climate conditions, and their income sensitivity can misrepresent the true impact on different households. Composite energy poverty indicators can be complex to construct and interpret, requiring extensive data that may not be uniformly available, and their weighting of components can be subjective, leading to potential bias. Indicator 3: HEP utilized a self-reported survey question which is at risk of respondent-related biases, which stem from the respondents' subjective perceptions and behaviors.

The study is also limited by GeoDa's LISA analysis, which is based on assumptions of stationarity, sensitivity to spatial scale, edge effects, data quality, and the complexity of result interpretation. LISA results can be sensitive to the number of permutations used and the significance level chosen. To mitigate this, several permutations were compared, and different significance filters were applied to assess the stability of the results. The RECS dataset used was highly aggregated, and future research using household level data could provide more nuanced results. A fourth energy poverty indicator including health impacts was intended to be used but a lack of data limited the inclusion of this indicator and therefore richer discussion of energy poverty and indicators to consider. Of note, this 2020 RECS dataset was published at the beginning of a global pandemic and several large-scale conflicts which could impact the proportion of households experiencing energy poverty. Despite these limitations, this study provides a useful starting point for understanding key considerations of spatial assessment and household traits around energy poverty measurement in the US context.

When different energy poverty indicators are used to analyze data, they identify varying spatial areas, highlighting the need for policymakers and stakeholders to comprehend the diverse scope and distribution of energy poverty in the U.S. The states identified as energy poor through the LISA analysis, section 4.2, were different between all three indicators. The states identified include Virginia (Indicator 1: >10%), North Carolina (Indicator 2: Mx2), along with New York and West Virginia (Indicator 3: HEP). The identified areas are where targeted interventions or policies may be needed to address the higher levels of energy poverty, compared to neighboring areas. For policymakers and researchers, understanding spatial analysis results is crucial as it informs where resources might be most effectively allocated to mitigate energy poverty. The varied spatial results underscore the importance of localized approaches and tailored strategies that account for regional disparities and conditions. Existing studies point to different indicators providing different results (see Siksnelyte-Butkiene et al., 2022 for an overview) and have emphasized the value of evaluating energy poverty through a multifaceted lens that considers various metrics (Sovacool and Dworkin, 2015; Bouzarovski & Petrova, 2015; Che et al., 2021).

The divergence in results between indicators and models in the logit regressions reveals significant variations in states' classification as energy poverty hotspots or cold spots, suggesting that regional factors and state-level characteristics may significantly influence energy poverty outcomes. For instance, states such as Georgia, Mississippi, and South Carolina were identified as hotspots in the >10% indicator, indicating higher likelihoods of energy poverty. In contrast, states like Maryland, Virginia, Kentucky, and North Carolina are classified as cold spots, suggesting lower energy poverty rates. These variations suggest regional, or state-level factors may play a role. The differences could be due to varying socio-economic conditions, climate, housing characteristics, or other state-specific policies and cultural factors that were not directly measured in the models (Pauchari et al., 2013; Bednar and Reames, 2020). Further investigation into states identified might reveal specific regional characteristics that contribute to the observed outcomes.

Kentucky and New York are less significant variables across all three indicators in the logit regression models. Therefore, there is potential to learn from what is, or is not, being done in these states. New York has numerous state and local energy policies and laws addressing energy which can be learned from. Of interest to other Appalachian states that are also major energy producers is Kentucky's current energy strategy, known as "KYE3: Designs for a Resilient Economy (State Energy Office, 2022)." The strategy implements regional considerations for Appalachia's unique position as a major energy producer with a strong focus on coal. The Appalachian region can seek to use Kentucky as a regional lighthouse to learn how their policies are attempting to balance economic development, energy security, and some degree of energy efficiency and environmental considerations.

Existing literature highlights that current research predominantly addresses energy poverty within the more geographically and climatically homogeneous context of Europe (Bednar and Reames, 2020). Consequently, there is a recognized necessity to develop theoretical and practical frameworks specific to the U.S. context (Jenkins et al., 2017; Kontokosta et al., 2020; Jones and Reyes, 2023). The spatial analysis conducted in this study aims to facilitate targeted energy policy interventions that can enhance the well-being of Appalachian residents and those in specific states. Recent studies have identified persistent high-poverty counties within Appalachia (Pollard et al., 2024). Analyzing county-level energy poverty and comparing it with existing spatial identifications of high-poverty counties could inform interventions best suited to these areas (Curtis et al., 2019; Lobao et al., 2016). This research extends prior work on the Netherlands by Mulder et al. (2023), on municipal-level assessments, and Mashhoodi et al. (2020), on urbanized areas, through the application of spatial analysis in the U.S. context.

Hidden energy poverty (HEP) is the composite indicator implemented in this study. Building from the identification of HEP as a phenomenon, a behavioral component was integrated into the study aligning with calls for more comprehensive approaches that consider behavioral, structural, and regional factors beyond traditional economic indicators (Karpinska and Śmiech, 2020; Betto et al. 2020; Cong et al., 2022). Existing studies on HEP not only focused on different regions but also different ways to pinpoint HEP. Karpinska and Śmiech (2020) presented a comprehensive approach for 11 Central and Eastern European countries, defining exposure to HEP with housing costs and income thresholds and Betto et al. (2020) which developed a new measure for Italian HEP, considering factors such as poor energy efficiency of buildings, poverty situation, low energy consumption, and climate sensitivity. Through the logit regression analyses, the HEP indicator is found to more likely impact those working full-time. HEP often affects full-time workers because their incomes may exceed eligibility thresholds for energy assistance programs, making them "invisible" to traditional poverty metrics (Cong et al., 2022). Additionally, they may engage in energy-restricting behaviors and live in poorly insulated or energy-inefficient housing, leading to higher relative energy costs despite seemingly adequate incomes (Eisfeld and Seebauer, 2022).

Analysis of what the variables and their results across the different indicators may mean in context is explored in the following section. Employment status, air conditioning, household composition, home age, energy assistance, geographic location, educational attainment, gender, and race are identified as significant depending on the specific indicator of energy poverty used.

Employment Status (EmployFullTime) emerges as a consistently significant predictor across all three indicators. In the context of the first indicator, which considers households spending more than 10% of their income on energy costs, employment status increases the likelihood of energy poverty. This contradicts common conceptions that those unemployed are more likely to be in energy poverty (van Ooij, 2023). From this, stable employment alone may not be sufficient to mitigate energy poverty in scenarios where energy costs are disproportionately high call for more nuanced surveys and use of composite energy poverty.

The role of air conditioning varies between indicators in the study. For the first indicator, the presence of air conditioning significantly decreases the likelihood of energy poverty, possibly due to its association with higher living standards and better-insulated homes. However, in the HEP indicator, air conditioning significantly increases the likelihood of energy poverty in Model 2, suggesting that households with air conditioning may face higher energy costs that compel them to cut back on other necessities. Air conditioning is not mentioned as a significant predictor in the Mx2 indicator, highlighting its variable influence depending on the specific context of energy poverty and substantiating not using it as a measure of energy poverty (Clancy et al., 2017; Snell et al., 2015; Middlemiss, 2020).

The household composition, particularly the number of household members (Numofmem), presents another point of contrast. In the >10% indicator, a larger number of household members significantly decreases the likelihood of energy poverty, possibly due to shared energy costs and economies of scale. This factor is not significant in the Mx2 indicator but becomes significant in Model 2 of the HEP indicator, where it increases the likelihood of energy poverty. The result from the Hidden Energy Poverty indicator is supported by literature where the number of household members is considered a significant factor in relation to energy poverty (Chen and Feng, 2022). More members of a household may exacerbate energy poverty risk for those already vulnerable (Karpinska and Śmiech, 2023). This suggests that the number of household members cannot clearly indicate energy poverty, but contextual factors should be considered in research and policy.

Energy assistance (ENERGYASST) is introduced into the logit regression in model 2 and is a critical factor in both the first and second indicators, where it significantly increases the likelihood of energy poverty. This counterintuitive finding may reflect the targeting of energy assistance programs towards households already experiencing severe energy insecurity. In the HEP indicator, energy assistance remains a significant predictor, underscoring its role in mitigating energy insecurity despite its association with higher reported rates of energy poverty. The second model includes the variable HomeTempWINTER which connects adjustments in temperature having a modest impact on the odds of being in energy poverty. The variable draftiness (DRAFTY) is self-reported information on home conditions. In Indicator 3 HEP emerges as a significant predictor of energy poverty, underscoring the importance of housing quality and programs targeting assistance in weatherization in addressing energy poverty.

Results from Indicator 1: >10% logit regressions demonstrate race may influence energy poverty. This builds on existing literature researching race and energy poverty in the different countries, such as the United States (e.g., Bouzarovski, 2014; Bouzarovski and Simcock, 2017; Memmott et al., 2021, Dogan et al., 2022) and South Africa (e.g., Lin and Okyere, 2023). Memmott et al. (2021) concluded that Black and Hispanic households are more vulnerable to energy insecurity and face utility disconnection in the U.S. Dogan et al. (2022) point to health and income as factors which influence African Americans likelihood to be in fuel poverty. Such results further strengthen the call for integrating energy poverty in policies and programs intended for social equity, economic stability and environmental sustainability (Pauchari et al., 2013; Bednar and Reames, 2020). To successfully integrate energy poverty mitigation efforts into wider policies, Bednar and Reames (2020) note the crucial need for formal recognition of energy poverty at the federal level. Further literature point to subsidy programs as ways to target and break the connection of race and energy poverty (Dogan et al., 2022). Specific recommendations include offering preferential discounted rates and facilitating easier access to energy for specific demographic groups (Dogan et al., 2022). However, studies outside of the U.S. have shown, through moderation analysis, that subsidies, social housing and free basic electricity in South Africa, are not effective in energy poverty reduction. Memmott et al. (2021) suggest moving beyond subsidies and focus on expanding clean energy services to non-whites.

In contrast to previous studies, females are found to be less likely to experience energy poverty in the >10% indicator. However, gender is not mentioned as significant factors in the Mx2 and HEP indicators, suggesting the variable influences energy poverty depending on the specific indicator of energy poverty used. Gender dimensions of energy poverty have been explored and identified as significant within the EU context (e.g., Zamfir, 2023; Feenstra and Clancy, 2020).

Finally, educational attainment shows a complex relationship with energy poverty. In Indicator 1: >10%, education levels, particularly for those without a high school diploma, significantly increase the likelihood of energy poverty. Similarly, Indicator 3 HEP results suggest that lower educational attainment is strongly linked to higher energy poverty risk. This could be linked to associated factors such as lower income and less energy-efficient homes, suggesting that lower educational attainment may be associated with higher vulnerability to energy costs. Existing studies linked lower educational levels to increased energy poverty in different countries, e.g., in the Netherlands (van Ooij, 2023) and in 30 developing countries (Apergis et al., 2022). These findings underscore the critical impact of educational background on energy expenditure patterns which should be further explored in the U.S focusing on the nuance required for policy intervention to address energy affordability.

The multifaceted nature of energy poverty, distinguished through these indicators, underscore the need for holistic policy interventions that address both socioeconomic disparities and housing infrastructure deficiencies. By targeting key predictors such as household size, education level, access to energy assistance programs, and housing quality, policymakers can develop more effective strategies to mitigate the adverse effects of energy poverty and promote energy equity within communities. However, continued research and data collection efforts are needed to refine existing indicators of energy poverty and inform the current interventions aimed at reducing energy insecurity and improving the overall well-being of vulnerable populations. The recent implementation in the U.S. of policies related to energy poverty (e.g., the Infrastructure Investment and Jobs Act of 2021, the Inflation Reduction Act) necessitates further exploration of the costs and distributional impacts of state-level initiatives, particularly their potential to exacerbate income inequality (Che et al., 2021). Of note is the introduction to the 118th Congress (2023-2024) of the Energy Poverty Prevention and Accountability Act of 2023 (H.R.5482) which aims to hold the administration accountable for energy policies that may disproportionately affect rural and low-income Americans. Ensuring equitable access to energy resources and addressing energy-related injustices are fundamental to addressing income inequalities and mitigating climate change. The disproportionately negative distributional impacts of existing climate policies can undermine their political viability and sustainability.

6. Conclusions and Recommendations

This thesis assessed energy poverty within the U.S, specifically focusing on the Appalachian region. It did so to explore if and where different indicators of energy poverty would identify areas as energy poor. Through the initial literature analysis of energy poverty indicators, the spatial distribution of three different indicators of energy poverty were assessed. Single indicators of energy poverty were used (>10% and Mx2 indicators) and based on insight from the literature, a composite indicator (HEP) was established using self-reported data from the RECS dataset (EIA, 2020). Further analysis of the data was done using the three energy poverty indicators to explore what household traits are associated with energy poverty in Appalachia. Two models were developed using the RECS survey results to delve into respondents reporting of experiencing energy poverty.

Energy poverty in the U.S. is measured through various indicators, each capturing different dimensions of the issue. Through the literature review, indicators were identified as single indicators, including income-based indicators (e.g., 2xM, LIHC, and AFC) and expenditure-based indicators (e.g., energy burden and > 10%), and composite indicators to capture multiple dimensions of energy vulnerability (e.g., MEPI). Subjective indicators focus on self-reported data like the inability to keep homes warm or utility bill arrears (e.g., HEP). Specific to the U.S. are the LIHEAP eligibility criteria and the Energy Insecurity Scale. Other indicators assess energy access, consumption, building characteristics, geographic clustering, and health-related impacts. Despite the lack of a single federal definition, these diverse indicators highlight the multifaceted nature of energy poverty. Researchers advocate for more comprehensive and multidimensional metrics, such as the "energy equity gap," to better capture energy poverty in low-income households (Cong et al., 2022).

Through the LISA analysis of homeowners within the 13 states of the Appalachian region, different spatial outliers are identified depending on the energy poverty indicator used. Virginia and North Carolina are identified as spatial outliers with high energy expenditures compared to their neighbors under the >10% and Mx2 indicators, respectively. New York and West Virginia are also noted as outliers in HEP. The LISA analysis indicates minimal spatial clustering of median energy expenditures among low-income homeowners in most states, suggesting that non-spatial factors are critical in addressing energy poverty. These findings underscore the importance of tailoring policy interventions to the specific socioeconomic contexts of each state to effectively address energy poverty.

The household traits analysis of the three energy poverty indicators underscores the importance of targeted policies to address energy poverty, considering the varying impacts of demographic, socioeconomic, and regional factors. These analyses reveal significant disparities in energy poverty indicators across household traits and regions in Appalachia. Educational attainment, household size, employment status, and the state of residence significantly influence the likelihood of experiencing high energy costs, excessive energy expenditure, or hidden energy poverty.

To effectively address energy poverty in the U.S., and more specifically within regions such as Appalachia, it is essential to establish clear goals and targeted policies, develop nuanced energy equity metrics that accurately capture behavioral complexities and policy implications, and enhance community engagement strategies to involve marginalized communities in decision-making processes. Furthermore, addressing the affordability of renewable energy technologies for low-income households and ensuring inclusive job creation opportunities in the renewable energy sector through accessible training programs are critical steps. Bridging these gaps is crucial for advancing energy justice, promoting equitable access to clean energy, and implementing comprehensive interventions to combat energy poverty (Jones and Reyes, 2023).

The research and analysis look to provide additional considerations for energy poverty policy development in the U.S. by considering multiple indicators of energy poverty. By focusing research on the Appalachian region, more targeted research and policy can help to lessen the longstanding socio-economic disparity in the region (Partridge et al., 2013; Department of Energy, 2020). Understanding the knowledge gaps regarding energy poverty in the U.S. is crucial for developing effective policies and interventions. Energy poverty remains a complex and multifaceted issue, exacerbated by several key knowledge gaps. One significant gap is in data availability and accessibility; comprehensive data on the extent, distribution, and contributing factors of energy poverty is often fragmented or lacking. Enhancing data collection methods and making data more accessible is crucial for better addressing this issue. Furthermore, there is a need for deeper understanding of the socioeconomic dynamics that contribute to energy poverty, including income levels, housing quality, and access to energy-efficient technologies. The health impacts of energy poverty, such as increased risks of respiratory illnesses from indoor air pollution, are recognized but require further quantification and exploration of potential interventions.

Evaluating the effectiveness of current energy assistance programs and policies is essential to inform future decisions. This involves assessing the reach, efficiency, and long-term impacts of these programs. Understanding the vulnerability and resilience of different populations, e.g., low-income households, minority communities, and the elderly, is also critical. Crucially, the addition of spatial consideration in evaluation of existing and planned energy assistance programs would provide clearer building blocks for allocating, or planning to allocate, resources. This knowledge can guide the development of targeted interventions to enhance resilience and reduce disparities.

Finally, exploring the intersection between energy poverty and climate change is vital for creating sustainable solutions. This includes understanding how climate change affects energy access and affordability and identifying opportunities for synergies between mitigation and adaptation efforts. Addressing these gaps through targeted research and policy initiatives can significantly advance efforts to alleviate energy poverty in places most vulnerable.

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8. Appendix

Table A1: Reportable domains of the Appalachian region and their median proportion of income spent on energy in the home considering owners and renters. Proportions in red already exceed the 10% indicator of energy poverty.

	State	ALL	Median proportion of income spent on energy in the home: Owners	Renters	Owners vs. Renters in median proportion of income spent on energy in the home	Electricity cent/kWh (2020)	Natural gas cent/kWh (2020)
1	Alabama	0.1018	0.0766	0.1836	0.107	10.38	3.76
2	Georgia	0.0794	0.0595	0.1326	0.0731	10.6	4
3	Kentucky	0.0623	0.048	0.1001	0.0521	9.46	3.2
4	Maryland	0.0522	0.0395	0.0812	0.0417	11.44	4.7
5	Mississippi	0.0821	0.0681	0.1349	0.0668	10.65	3.58
6	New York	0.0643	0.0484	0.0926	0.0442	18.58	5.87
7	North Carolina	0.0567	0.0474	0.0815	0.0341	9.8	3.85
8	Ohio	0.0586	0.0488	0.0893	0.0405	9.88	3.3
9	Pennsylvania	0.0531	0.0467	0.0552	0.0085	10.01	3.55
10	South Carolina	0.059	0.0524	0.0802	0.0278	10.4	4.05
11	Tennessee	0.0705	0.056	0.1053	0.0493	9.59	3.65
12	Virginia	0.0496	0.0469	0.0575	0.0106	9.63	3.75
13	West Virginia	0.0777	0.0636	0.1219	0.0583	9.41	3.57
	Total Median	**0.0623**	**0.0488**	**0.0926**	**0.0442**	**10.01**	**3.75**

Table A2

Full table from Table 2 including all Income Decile and low-income homeowners and renters

Income Decile		D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15	D16
Average Income		$2,500.00	$6,249.50	$8,749.50	$11,249.50	$13,749.50	$17,499.50	$22,499.50	$27,499.50	$32,499.50	$37,499.50	$44,999.50	$54,999.50	$67,499.50	$87,499.50	$124,999.50	-
Owners																	
% Low Income		100%	100%	100%	100%	100%	100%	100%	100%	0%	0%	0%	0%	0%	0%	0%	0%
Energy Cost > 10%	*and Low income*	99.44%	93.24%	87.36%	83.08%	54.45%	45.45%	23.76%	12.18%	6.90%	4.51%	0.77%	0.80%	0.32%	0.10%	0.00%	0.04%
Energy Cost > Mx2	*and Low income*	5.06%	2.70%	3.45%	3.59%	1.05%	1.62%	3.76%	3.57%	4.60%	5.10%	4.07%	4.71%	5.97%	8.44%	10.74%	21.20%

HEP	*and Low income*	40.45%	47.30%	43.68%	41.03%	34.55%	26.95%	27.13%	24.58%	19.82%	19.61%	17.38%	15.01%	11.48%	8.55%	5.05%	2.30%
Renters																	
% Low Income		100%	100%	100%	100%	100%	100%	100%	100%	0%	0%	0%	0%	0%	0%	0%	0%
Energy Cost > 10%	and Low income	99.15%	87.32%	62.35%	46.15%	30.63%	18.55%	11.59%	5.52%	3.13%	1.76%	0.23%	0.00%	0.00%	0.00%	0.00%	0.35%
Energy Cost > Mx2	and Low income	2.56%	0.70%	1.23%	0.45%	1.25%	1.21%	0.91%	1.38%	2.81%	2.11%	2.09%	1.89%	2.33%	3.52%	4.36%	6.71%
HEP	and Low income	47.01%	45.77%	43.21%	43.44%	40.63%	39.11%	42.38%	38.62%	38.75%	37.32%	31.86%	28.92%	21.40%	14.73%	9.23%	4.95%

Table A3: The median energy expenditure of low-income homeowners in energy poverty across the three indicators of energy poverty.

State	State Postal Code	M1) > 10%	M2) Mx 2	M3) HEP
Alabama	AL	$ 2,453.79	$ 4,547.55	$ 2,219.85
Georgia	GA	$ 2,323.64	$ 4,261.92	$ 2,179.43
Kentucky	KY	$ 2,059.12	$ 4,015.03	$ 1,772.56
Maryland	MD	$ 2,043.02	$ 4,810.00	$ 1,488.61
Mississippi	MS	$ 2,058.48	NA	$ 1,819.88
New York	NY	$ 2,593.30	$ 4,324.50	$ 2,720.71
North Carolina	NC	$ 2,244.30	$ 4,775.74	$ 1,669.41
Ohio	OH	$ 2,525.76	$ 4,244.75	$ 1,139.68
Pennsylvania	PA	$ 2,380.13	$ 3,853.95	$ 2,284.50
South Carolina	SC	$ 2,322.55	$ 3,812.42	$ 3,942.98
Tennessee	TN	$ 2,062.20	$ 3,841.97	$ 1,941.87
Virginia	VA	$ 2,406.42	$ 3,837.34	$ 1,778.51
West Virginia	WV	$ 2,530.64	$ 4,268.24	$ 2,071.87
	Median Total	$ 2,323.64	$ 4,253.34	$ 1,941.87

Table A4: Queen's contiguity matrix for the states that contain parts of the Appalachian region.

State	AL	GA	KY	MD	MS	NY	NC	OH	PA	SC	TN	VA	WV	Number of neighbors
AL	1	1	0	0	1	0	0	0	0	1	1	0	0	5
GA	1	1	0	0	0	0	1	0	0	1	1	0	0	5
KY	0	0	1	0	0	0	1	1	0	0	1	1	1	6
MD	0	0	0	1	0	0	0	0	1	0	0	1	1	4
MS	1	0	0	0	1	0	0	0	0	0	1	0	0	3
NY	0	0	0	0	0	1	0	1	1	0	0	0	0	3
NC	0	1	1	0	0	0	1	0	0	1	1	1	0	6
OH	0	0	1	0	0	1	0	1	1	0	0	0	1	5
PA	0	0	0	1	0	1	0	1	1	0	0	0	1	5
SC	1	1	0	0	0	0	1	0	0	1	1	0	0	5
TN	1	1	1	0	1	0	1	0	0	1	1	1	1	9
VA	0	0	1	1	0	0	1	0	0	0	1	1	1	6
WV	0	0	1	1	0	0	0	1	1	0	1	1	1	7

Table A5: Weights Matrix Row Standardized where each weight is divided by number of neighbors, so each row sums to 1.

State	AL	GA	KY	MD	MS	NY	NC	OH	PA	SC	TN	VA	WV	Row Sum
AL	0.20	0.20	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.20	0.20	0.00	0.00	1
GA	0.20	0.20	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.20	0.20	0.00	0.00	1
KY	0.00	0.00	0.17	0.00	0.00	0.00	0.17	0.17	0.00	0.00	0.17	0.17	0.17	1
MD	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.25	0.25	1
MS	0.33	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	1
NY	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.33	0.33	0.00	0.00	0.00	0.00	1
NC	0.00	0.17	0.17	0.00	0.00	0.00	0.17	0.00	0.00	0.17	0.17	0.17	0.00	1
OH	0.00	0.00	0.20	0.00	0.00	0.20	0.00	0.20	0.20	0.00	0.00	0.00	0.20	1
PA	0.00	0.00	0.00	0.20	0.00	0.20	0.00	0.20	0.20	0.00	0.00	0.00	0.20	1
SC	0.20	0.20	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.20	0.20	0.00	0.00	1
TN	0.11	0.11	0.11	0.00	0.11	0.00	0.11	0.00	0.00	0.11	0.11	0.11	0.11	1
VA	0.00	0.00	0.17	0.17	0.00	0.00	0.17	0.00	0.00	0.00	0.17	0.17	0.17	1
WV	0.00	0.00	0.14	0.14	0.00	0.00	0.00	0.14	0.14	0.00	0.14	0.14	0.14	1

Table A6:Variables encompassing household traits of energy poverty used in Model 1 and 2 for the logit regressions.

Variable NAME	Description (Based on RECS 2020 codebook)
TotalDOL	Total cost including electricity, natural gas, propane, and fuel oil, in dollars, 2020
AirCond	= 1 if the household has air conditioning and 0 otherwise.
SingleFamily	= 1 if Single-family house detached from any other house or Single-family house attached to one or more other houses (e.g., duplex, row house, or townhome)
HomeAge	Range when housing unit was built "1 Before 1950, 2 1950 to 1959, 3 1960 to 1969,4 1970 to 1979, 5 1980 to 1989, 6 1990 to 1999, 7 2000 to 2009, 8 2010 to 2015, 9 2016 to 2020"
NumHH	Number of household members (top-coded) for the range of 1 - 7
TotalSqFt	Total energy-consuming area (square footage) of the housing unit.
HDD65	Heating degree days in 2020, base temperature 65F
CDD65	Cooling degree days in 2020, base temperature 65F
Gender	= 1 if Female
Race	Householder (respondent) race
Age	Respondent age (top-coded)
Over65	Number of household members aged 65 or older: '0 - 6
AtHome	Number of weekdays someone is at home most or all day
Education	
education(1)	1 Less than high school diploma or GED
education(2)	2 High school diploma or GED
education(3)	3 Some college or associate's degree
education(4)	4 Bachelor's degree
Employment	Respondent employment status where: 1 Employed full-time 2 Employed part-time 3 Retired 4 Not employed
UATYP10	2010 Census Urban Type Code includes C = Urban cluster, R = Rural area, U = Urban area
U	= 1 if part of an Urban area
R	= 1 if part of a Rural area
State Postal	Postal codes associated with the states in the Appalachian region
Model 2	
HomeTempWINTER	Respondent reported winter thermostat setting or temperature in home when someone is home during the day.
HomeTempSUMMER	Respondent reported summer thermostat setting or temperature in home when someone is home during the day.
DRAFTY	= 1 if respondent responded "How often home is drafty" with: 1) All the time, 2) Most of the time, 3) Some of the time
ADQINSUL	=1 if respondent answers that the home is well or adequately insulated. =0 if poorly insulated or if there is no insulation.
ENERGYASST	= 1 if ever participated in home energy assistance program. From personal correspondence with the RECS survey managers, assistance is a non-defined term.